Predicting Global Disposition of U.S. Military Personnel via Open-Source, Unclassified Means

THESIS

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Abstract

The Joint Distribution Processing Analysis Center (JDPAC) of the United States Transportation Command (USTRANSCOM) regularly forecasts the demand of USTRANSCOM assets required by geographic and combatant commanders. These demands are subject to fluctuations due to unforeseen circumstances such as war, conflict, natural disasters, and other calamities requiring the presence of military personnel. This study evaluates the use of exponential state space smoothing, ARIMA, and Regression with ARIMA errors models to forecast the number of military personnel expected in each country, for a test set of countries of interest to USTRANSCOM and which manifest a high degree of variability in the anticipated number of troops each year. The expectation by USTRANSCOM is that accurate forecasts for the number of military personnel in each country can be leveraged to develop alternative transportation workload forecasts of demand of USTRANSCOM assets.

There was not a single model that performed best for all countries and branches of service. Each model was analyzed via the traditional 80/20 forecasting evaluation metric as well as a two-year horizon cross-validation metric. The exponential smoothing model with a high level of α performed quite well for many of the models, indicating that perhaps simpler models will still provide accurate forecasts. Further research is needed to determine whether incorporating forecasts of military personnel will improve the ability to forecast demand of USTRANSCOM assets.

Dedicated to my wonderful wife and daughter

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PREDICTING GLOBAL DISPOSITION OF U.S. MILITARY PERSONNEL VIA OPEN-SOURCE, UNCLASSIFIED MEANS

I. Introduction

1.1 Background

This research examines forecasting models for U.S. military troop strength, by country, in support of the United States Transportation Command (USTRANSCOM). USTRANSCOM, headquartered at Scott Air Force Base, Illinois, is charged with delivering military personnel, weapon systems, and supplies around the world. This research is sponsored by USTRANSCOM's Joint Distribution Processing Analysis Center (JDPAC).

USTRANSCOM is a unified, functional combatant command that provides support to the eight other U.S. combatant commands, the military services, defense agencies, and other government organizations [28]. USTRANSCOM's vision is to be the transportation and enabling capability provider of choice. Its mission is to provide full-spectrum global mobility solutions and related capabilities for supported customers' requirements in peace and war. USTRANSCOM operates around the globe, combining the forces of Soldiers, Sailors, Airmen, Marines, Coast Guardsmen, Department of Defense (DOD) civilians and commercial partners to execute a wide array of joint mobility missions. In September 2003, USTRANSCOM became the single entity to direct and supervise the strategic distribution system for the DOD. USTRANSCOM's total wartime capability is comprised of a diverse force consisting of 45,945 active duty; 73,058 Reserve and Guard, and 19,104 civilian personnel.

During an average week, USTRANSCOM conducts more than 1,900 air missions, 25 ships underway, and 10,000 ground shipments operating in 75 percent of the world's countries.

This dynamic environment puts pressure upon USTRANSCOM to ensure an accurate workload and corresponding expenses forecast. USTRANSCOM transportation related activities are funded using the Transportation Working Capital Fund (TWCF). The TWCF is an account from which USTRANSCOM pays contracted shippers, into which USTRANSCOM receives payments from DoD customers, and which acts as a buffer to absorb any deficit or surplus in revenue collected in a given year, vis-à-vis the actual costs incurred. The costs charged to USTRANSCOM by contracted shippers vary somewhat between shipping agents and individual contracts. On an annual basis, USTRANSCOM determines the shipping rates that DoD customers must pay, in dollars per measurement ton (mton) and discretized by the combination of the origin, destination, the type of commodity being shipped, the container size, and the booking terms (i.e., whether a customer will ship from/to an inland base or a seaport and, if shipping from/to a seaport, whether the loading/unloading will be performed by the customer or contracted stevedores). To calculate such rates, USTRANSCOM uses an adjusted expected cost model wherein, for each combination-specific rate, they compute the average cost per mton in the current year, adjust it for inflation, and then adjust it once again with a mark-up to account for a fixed amount of overhead costs in a given year. USTRANSCOM seeks to neither earn nor lose money from the TWCF in a given year, unless the TWCF balance has become too high/low, at which point an additional mark-down/up is applied to all rates to affect the desired adjustment.

A key element of managing the TWCF and determining the variable mark-up for all rates to account for a fixed set of overhead costs is to accurately forecast shipping volumes in the upcoming years. Moreover, approximately 40% of shipping volume via liners (i.e., seagoing craft) is conducted to sustain deployed U.S. forces. As such, USTRANSCOM tasked one of its organizations, JDPAC, to improve forecasting activities related to the TWCF. JDPAC provides analysis and engineering support necessary for worldwide transportation of government assets.

JDPAC's Operations Support Division (TCAC-O) has collaborated with the Air Force Institute of Technology's Department of Operations Sciences (AFIT/ENS) to improve mission efficiency through collaborative research. Past studies have examined demand workload of the SAAM/Contingency airlift missions [5], optimizing forecasting associated with railway demands [23], and others [10]. By improving forecasting of demand workload, JDPAC hopes to mitigate the erratic behavior exhibited by the TWCF. (e.g., Some years JDPAC underforecasts demand workload while other years it overforecasts demand workload). By mitigating this erratic behavior, it will improve consistency of the rates and ensure customers are paying only for what they use. The scope of this research is to forecast the U.S. military force strength for each country in the expectation that having an accurate prediction of the military force strength for each country will enable improved forecasting of workload demand.

1.2 Problem Statement

The problem statement is summarized as follows:

We seek to develop and test a suite of predictive models and recommend an accompanying, robust model selection process to generate accurate forecasts of US military force strength, by country.

1.3 Thesis Organization

The remainder of this thesis is organized as follows: Chapter II highlights findings from a review of literature pertaining to forecasting methods and best practices. Following the literature review, Chapter III discusses the forecasting mechanisms including their terminology, parameters, assumptions, and limitations. The results are then presented in Chapter IV prior to concluding in Chapter V with insights and recommendations for future work.

II. Literature Review

2.1 Overview

A time series is a group of observations taken, in order, over a period of time. Time series data are used frequently to examine processes and phenomena in fields ranging from business to engineering to social sciences. An inherent aspect of time series data is that the observations are dependent upon the prior observation [4]. Forecasting using time series data accounts for this dependency and allows for predicting future observations based upon past observations.

An assumption of regression methods requires that observations are independent; however, this assumption is often violated. It is common for time-ordered error terms to be autocorrelated. There are two types of autocorrelation: positive autocorrelation and negative autocorrelation. Positive autocorrelation exists when a positive (negative) error in time period t tends to produce another positive (negative) error term in a later time period. Negative autocorrelation exists when a positive (negative) error term in time period t tends to produce a negative (positive) error term in a subsequent time period.

Bowerman [3] identifies four components to time series analysis: the trend, cycle, seasonal variations, and irregular fluctuations. The trend refers to whether the data observations increase or decrease over time. The cycle refers to recurring upward or downward movements around the trend levels. The seasonal variations are periodic patterns which occur within a calendar year. Irregular fluctuations are inexplicable movements in a time series.

Box defined five important practical problems which depend upon time series analysis. A summary of the problems are provided in this section, and an interested reader is directed to the work by Box [4] for additional information. The first problem

Box identified for time series analysis is that of forecasting future values utilizing past values. The second problem is to determine transfer functions to study process dynamics. Third, Box noted that utilizing time series analysis allows one to study intervention events, which he defined as exceptional external events, such as a policy changes or worker strikes, and which could affect the observation values of the time study under consideration. Fourth, analysis of multivariate time series allows for studying the dynamic relationships among several time series that affect the forecasted observation values. Finally, Box stated that time series are important to statistical process control and allow a process manager to examine, “when did a change occur?” and subsequently “why did a change happen?”.

Time series analyses are performed using stochastic models. A subcomponent of stochastic models addresses stationary and nonstationary processes. Stationary models vary about a fixed mean with constant variance. Nonstationary models have no constant mean level. It has been shown that many of the original economic forecasting methods using exponentially weighted moving averages are appropriate when modeling particular nonstationary processes [4]. Exponentially weighted moving average forecasts are members of a class of nonstationary processes known as autoregressive integrated moving average processes.

There has been limited research published in the open literature regarding the forecasting of military troop levels by country. The current literature most specific to the forecasting of troop levels to date has been performed by Kane [17]. Kane used two separate autoregressive models as well as a simple linear forecasting model to collectively predict that the level of troops worldwide has been trending downwards since the 1950s and is predicted to reach zero troops deployed worldwide by 2045 and zero active duty troops by 2060. Whereas Kane performed a high-level analysis on the number of troops deployed, the analysis in this paper will be a lower-level analysis of the troop level, by country and service.

2.2 Autoregression

An autoregressive model utilizes a value from a time series to regress previous values for that same time series. The autoregressive model is similar to a linear regression model, where the index i is replaced by the index t. The first order autoregression has the form given by $y_t = \phi_0 + \phi_1 \cdot y_{t-1} + \varepsilon_t$.

Additional variables can be added to include regressors from previous time periods. For instance, if seeking to include the data from two time periods ago, such a model utilizes a second-order autoregression and is denoted as AR(2) given as $y_t = \phi_0 + \phi_1 \cdot y_{t-1} + \phi_2 \cdot y_{t-2} + \varepsilon_t$. This process can continue *ad infinitum* and a p-period model is generally written as AR(p).

2.3 Moving Average

In cases wherein the mean of a time series remains constant, that is to say that there is no trend to the time series and no seasonal pattern present, a moving average may work well. Two competing aspects of the moving average method are (1) to take enough observations such that we see a true estimate of the demand while also (2) providing enough weight to recent observations so as to remain relevant. According to Brown [7], the two points of consideration when developing moving average forecasting models are the (1) response to changes in demand and (2) error in measuring the average.

Brown [7] lists three standard kinds of change in demand: an impulse, a step, and a ramp. An impulse is a short term change in demand, a step is a permanent increase in demand, and a ramp is a steady upward trend in demand. The moving average handles each of these standard changes. If the standard change is an impulse, the effect will be that the average will increase by the pulse multiplied by $1/N$ and the increase will last for N periods where N is the number of periods included in the average. Thus the effect of a surge in demand is minimized when the average is computed over a very long period. If the standard change is a step, then the moving average will gradually adjust to the new step over a period of N. If the standard change is a trend, then the moving average will lag behind a certain number of periods based upon N.

There are several different moving averages with respect to forecast terminology. The aforementioned moving average is one which is not utilized to directly forecast a time series, but rather is utilized as a means of decomposing the time series into the time series components: cycle, trend, irregularity, and seasonality. It can be utilized as a forecast if it is believed that the current moving average is indicative of future observations.

A different moving average is presented in the ARIMA model developed by Box [4]. For the ARIMA model, the moving average is based upon past errors and utilizes a θ model parameter to adjust how much these past errors will impact future predictions. The equation when dealing with ARIMA models $y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q e_{t-q}$.

2.4 Differencing

The classical Box-Jenkins models describe stationary time series. A stationary time series is one in which the mean and the variance are both constant over time [3]. Conversely, a nonstationary time series is one in which the observations do not fluctuate about a fixed mean with a constant variance. For nonstationary time series, one must transform the nonstationary time series into a stationary time series. The typical method to accomplish this is to take the two first differences of the nonstationary time series values. The mathematical formula for taking the first differences of a time series is given by $z_t = y_t - y_{t-1}$ where $t = 2, \ldots, n$.

Unfortunately, taking first differences of nonstationary time series values does not always yield stationary time series values. For such cases, we must use other forms of differencing to produce stationary time series values. Sometimes, we are able to take the second differences, which are the first differences of the first differences, of the original time series values. The formula necessary to take the second differences of time series data is $z_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) = y_t - 2 \cdot y_{t-1} + y_{t-2}$ for $t = 3, 4, \ldots, n$

Empirical observation has shown that, if the original time series values $y_1, y_2, \ldots, y_n$ are nonstationary and nonseasonal, either the first differencing transformation or the second differencing transformation will usually suffice to attain stationary time series values. The subsequent sections of this literature review will explore nonstationary stochastic processes using the ARIMA model and the ARIMAX model.

2.5 ARIMA

An autoregressive integrated moving average (ARIMA) model allows for the estimation of a nonstationary stochastic process. ARIMA models rely upon their own historical data in order to predict future observations. This method allows for excellent flexibility when analyzing various time series and achieves high accuracy [9]. The ARIMA model was first introduced by Box and Jenkins in 1976 and is known as the Box-Jenkins methodology [9]. The model is denoted as ARIMA(p,d,q) and has the form given by $\Phi_p(B) \bigtriangledown^d x_t = \alpha + \Theta_q(B)\varepsilon_t$.

The term x_t is the measurement of the signal at time t, and ε_t represents the error term in the model [8]. The d-parameter represents the degree of differencing. The parameter B is defined as the backshift operator given by $B^k x_t = x_{t-k}$. The terms $\Phi_p(B)$ and $\Theta_q(B)$ are the autoregressive and moving average operators, respectively.

The mathematical equations for the autoregressive and moving average operators are respectively defined in Equations (1) and (2).

$$\Phi_p(B) = 1 - \Phi_1 B - \Phi_2 B^2 - \ldots - \Phi_p B^p \tag{1}$$

$$\Theta_q(B) = 1 - \Theta_1 B - \Theta_2 B^2 - \ldots - \Theta_q B^q \tag{2}$$

2.6 ARIMAX

ARIMAX is a form of ARIMA modeling that includes exogeneous variables, variables that are external to the prediction. For a generalized mathematical formulation of the ARIMAX model, an interested reader is directed to work by Newsham and Birt [22].

DeFelice [8] examined the use of numerical weather systems to perform load forecasting via ARIMAX models for electrical systems. DeFelice noted that the predicted temperature improves the load forecasting for Italy's power network. DeFelice considered several weather variables, temperature, windspeed and direction, relative humidity, and surface pressure, when attempting to examine which variables may be important in their relationship to energy demand, but the author concluded that only temperature influenced the daily energy load requirements. This work provides a simple, yet elegant, application of ARIMAX modeling to improve prediction accuracy.

Other ARIMAX models in the area of forecasting energy use include building-level occupancy data as exogenous variables. Newsham and Birt [22] showed that, by using occupancy data from carbon-dioxide sensors positioned in a circulation area, contact closure sensors, PIR motion sensors, and network activity, the forecast for energy demand can be improved. The results provided in the authors' study suggest that other large-scale buildings should consider investing in energy use forecasting that incorporates exogenous variables. In the research, these findings lend credence to the idea that exogenous variables should be considered when performing model building, as they may improve model performance.

ARIMAX has also been utilized for temporal modeling of forecasting and prediction of malaria infections in endemic districts of Bhutan. Wangdi et al. [29] showed that the exogenous variable of mean maximum temperature is a strong positive predictor of increased malaria reports two months later. Additionally, the authors developed specific models for each district. This concept was written about by Briet et al. [6] and is referred to *heterogenity*. The use of different models based on the concept of heterogenity minimized model error for malaria predictions in Sri Lanka. In this example, heterogenity is the idea that each region has different malaria level trends. Due to the heterogenity exhibited by different regions, it is prudent to utilize multiple lower-level ARIMA models rather than one higher-level ARIMA model for forecasting. This characteristic will be analogous to the level of troop presence for each country; certain countries are likely to have different trends in troop levels than other countries.

There have been several papers comparing ARIMA and ARIMAX models. Durka [9] examined the use of ARIMA vs ARIMAX modeling to analyze and forecast macroeconomic time series data and concluded that ARIMA performs slightly better for the dataset in question, for which GDP per capita is the output data and unemployment data is the input data. Durka's conclusion showed that, while more complex forecasting methods can be useful for certain datasets, the simpler model my perform better. A counterpoint to this argument is provided by Pektas and Cigizoglu [24] who evaluated the performance of ARIMA, ARIMAX, Artificial Neural Networks (ANN), and Hybrid models to predict the runoff coefficient for seven neighboring sub-basins around Ceyhan and Seyhan River in Turkey. Pektas and Cigizoglu showed that the

ARIMAX model outperformed the ARIMA model. Similarly, the multivariate ANN models performed better than the univariate ANN models developed. Finally, the Hybrid model utilized by Pektas and Cigizoglu predicted the peaks of the data with correct timing rather than before or after the spike, as done in the ANN, ARIMA, and ARIMAX models.

An additional ARIMAX model application is given by Williams [30], who examined the flow of traffic variables for highway data in France. The exogenous variables for this model included sensor data from upstream highway areas to predict traffic flow downstream. Williams' testing showed that the ARIMA model performed better than the ARIMAX model.

These examples illustrate what appears to be a dichotomy in the model performance. More complex models are worth exploring where possible, but they do not necessarily portend more accurate forecasts.

2.7 Exponential Smoothing

The Simple Exponential Smoothing method is a method whereby the forecast takes into account all previous observations and applies a greater weight to the more recent observations. Lower values of the model's paramter, α, provide a more stable forecast, whereas higher values of α provide a forecast that is more responsive to recent data fluctuations. The range for α is $0 \leq \alpha \leq 1$ and equation (3) shows the format for which each value of y_T is utilized in order to predict the future value, $\hat{y}_{T+1|T}$ [13]. As shown, a value of α set to one will only consider the immediately preceding value to predict the next value.

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \alpha(1-\alpha)^3 y_{T-3} + \cdots \tag{3}$$

The forecasts generated by this method are steady state forecasts; therefore, if any trend or seasonal component is present, the forecast will not necessarily perform well for a long forecast horizon. However, for a short term forecast horizon this should not present a cause for concern.

If the data exhibit trends, then a modification of the Exponential Smoothing Model using the Holt's Linear Trend Method can be implemented. Holt's Method allows for a trend when generating the forecast [13]. The Forecast equation below shows Holt's Method for forecasting a time series. Holt's Method is comprised of the level equation which was introduced in equation (3) and adds in the Trend equation. The h parameter in the Trend equation is the forecast horizon or the particular time period of interest. For instance, if interested in a forecast two time periods out, then h would be set to 2.This method shows that we have two smoothing parameters. The α smoothing parameter represents the level smoother. The β smoothing parameter applies to the trend. The forecast with the Holt method can be considered a linear function of h.

$$\begin{aligned} \text{Forecast equation} \qquad & \hat{y}_{t+h|t} = \ell_t + hb_t \\ \text{Level equation} \qquad & \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\ \text{Trend equation} \qquad & b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \end{aligned}$$

Exponential smoothing methods are not limited to merely the Simple Exponential Smoothing Method and Holt's Method. Indeed, by considering combinations of the trend and seasonal components, there are nine exponential smoothing methods possible [13]. These are given in Table 1.

These models can be combined with consideration of the model type with A for additive and M for multiplicative. For instance, if the models are multiplicative, then

Table 1: Classification of Exponential Smoothing Methods as Adapted from Hyndman

Trend Component	Seasonal Component		
	N(None)	A (Additive)	M (Multiplicative)
N (None)	(N,N)	(N,A)	(N,M)
A (Additive)	(A,N)	(A,A)	(A,M)
A_d (Additive damped)	($\mathrm{A_d}$,N)	($\mathrm{A_d}$,A)	($\mathrm{A_d}$,M)

we could classify a Simple Exponential Smoothing model as (M,N,N). These models are utilized in the **R** *ets* forecasting algorithm from the **forecast** package developed by Hyndman [11].

2.8 Measuring Forecast Errors

When model building, there are no universally acceptable criteria to determine whether or not a model is good enough. A good model will vary depending on the field; however, a key concept when building models is to maintain a goal of parsimony in which the simplest model that explains most of the variability exhibited by the data is generally the preferable model [13, 19].

When evaluating a forecast, there are several different measures one might use to evaluate its effectiveness. For any model, the forecast error can be calculated using the formula $e_t = y_t - \hat{y}_t$.

For a reader knowledgeable with linear regression, they will notice that this one-period-out forecast error is similar to a residual. Once the forecast error has been calculated, additional measures such as the ones identified below can be used to compare forecast accuracy from one model to the next. The list below is not an exhaustive list of accuracy measures, but it merely highlights those utilized to analyze the model forecasts in this thesis.

Hyndman [13] states that "when comparing forecast methods applied to a single time series, or to several time series with the same units, the MAE is popular as it

Table 2: Forecast Accuracy Metrics

Metric	**Equation**
Mean Absolute Error (MAE)	MAE $=\mid \frac{1}{T}\sum_{t=1}^{T} y_t - \hat{y}_t \mid$
Mean Absolute Scaled Error (MASE)	MASE $= \frac{1}{T}\sum_{t=1}^{T} \frac{e_j}{\frac{1}{T-1}\sum\limits_{t=2}^{T} \lvert y_t - y_{t-1} \rvert}$

is easy to both understand and compute." A disadvantage of the MAE is that it is scale dependent. In order to overcome the dependency, Hyndman and Koehler [15] recommend that the MASE be utilized to scale the errors based upon the training MAE from a simple forecast method. This approach allows q_j to be independent of the scale of the data.

A traditional forecast evaluation separates the data such that 80% of the data fall into the training set and 20% fall into the test set. While this benchmark is useful to ascertain how well the model performs over a long period of time, a more sophisticated measure of assessing the model is to utilize a measure commonly referred to as cross-validation or "rolling forecasting origin" [2].

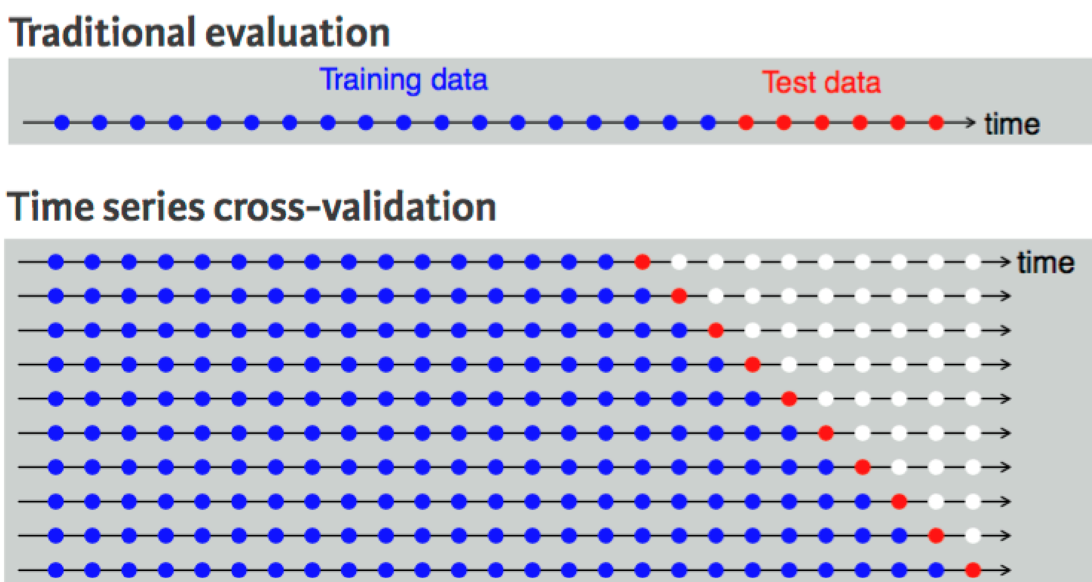


Figure 1: Traditional vs. Cross-Validation Evaluation [2]

The cross-validation methodology is useful when the forecaster is interested in a specific time period of forecast. If the forecaster desires an accurate forecast for a two-year forecast horizon, then evaluating the models' accuracies via the cross-validation accuracy would provide a more applicable metric than using the traditional forecast evaluation method.

III. Modeling Scope and Methodology

3.1 Model Scope

Countries.

The selection of countries to model in this research was based upon several characteristics of the data. The longevity of the data availability was important. If a country did not have data collected over an extended period of time, it was not modeled. For instance, several countries were only reported by Defense Manpower Data Center, an online repository containing historical worldwide troop data from 1950 to present, for one or two years and were therefore excluded from modeling. Additionally, if a country did not have data modeled for the past decade, it was not modeled because the country was deemed not to have a significant troop presence at the current time.

We selected countries to model based upon two criteria. First, the country should have a troop presence that is non-trivial; that is, it should have an enduring non-zero valued troop presence for at least the most recent 10 years of data. This criterion prevents the application of effort to forecast troop levels for countries that are pathologically challenging, without sufficient benefit for identifying accurate forecasts. Second, the country should have a relatively high variance for the troop presence when compared to other countries. Without this criterion, there is little challenge to forecasting; a steady-state, enduring troop presence is relatively easy to predict and cannot inform the models of interest for this study: those that seek to predict troop presence that varies and, in particular, troop presence that may vary as predicted by exogenous predictors rather than just historical troop levels alone.

In addition to the modeling of selecting countries identified via the criterion specified in the previous paragraph, JDPAC was specifically interested in forecasting models for the following countries: Japan, South Korea (i.e., the Republic of Korea), Germany, United Kingdom, Kuwait, Qatar, Saudi Arabia, and Bahrain [27].

The Venn Diagram in Figure 2 depicts the countries having a high observed variance in the amount of US military presence. The data, organized by three subsets: left, center, and right, are separated into countries which exhibited a high variance only historically (i.e. 1950-2002), countries which exhibited a high variance both historically and recently (i.e. 2003-2016), and countries which have exhibited a high variance only recently, respectively.

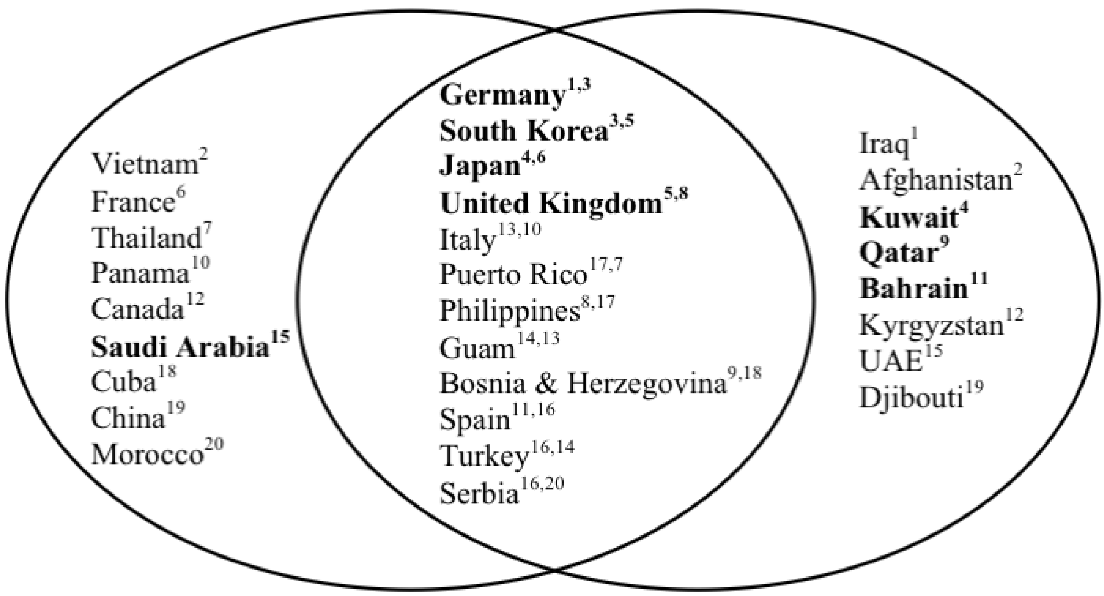


Figure 2: Countries Exhibiting High Variance

The countries are sorted within the subsets in Figure 2 such that the countries with the highest observed variance are at the top of each column while countries with lower variance are towards the bottom of each column. Countries written in boldface were on the list of countries of specific interest to JDPAC [27]. The superscript represents the ordinal ranking of the country within either the historically or recently high variance countries with 1 being the highest variance and 20 being the lowest variance. For the center column, the superscript number to the left of the comma represents the historical variance ranking, while the number to the right of the comma represents the recent variance.

Based upon Figure 2, the countries Saudi Arabia, Germany, South Korea, Japan, United Kingdom, Kuwait, Qatar, Iraq, Afghanistan, and Bahrain were all selected for study. This selection allowed for countries from each of our categories to be considered and also accounts for countries deemed important according to JDPAC. Figure 3 provides a graphical representation of troop levels by service for each of these ten countries.

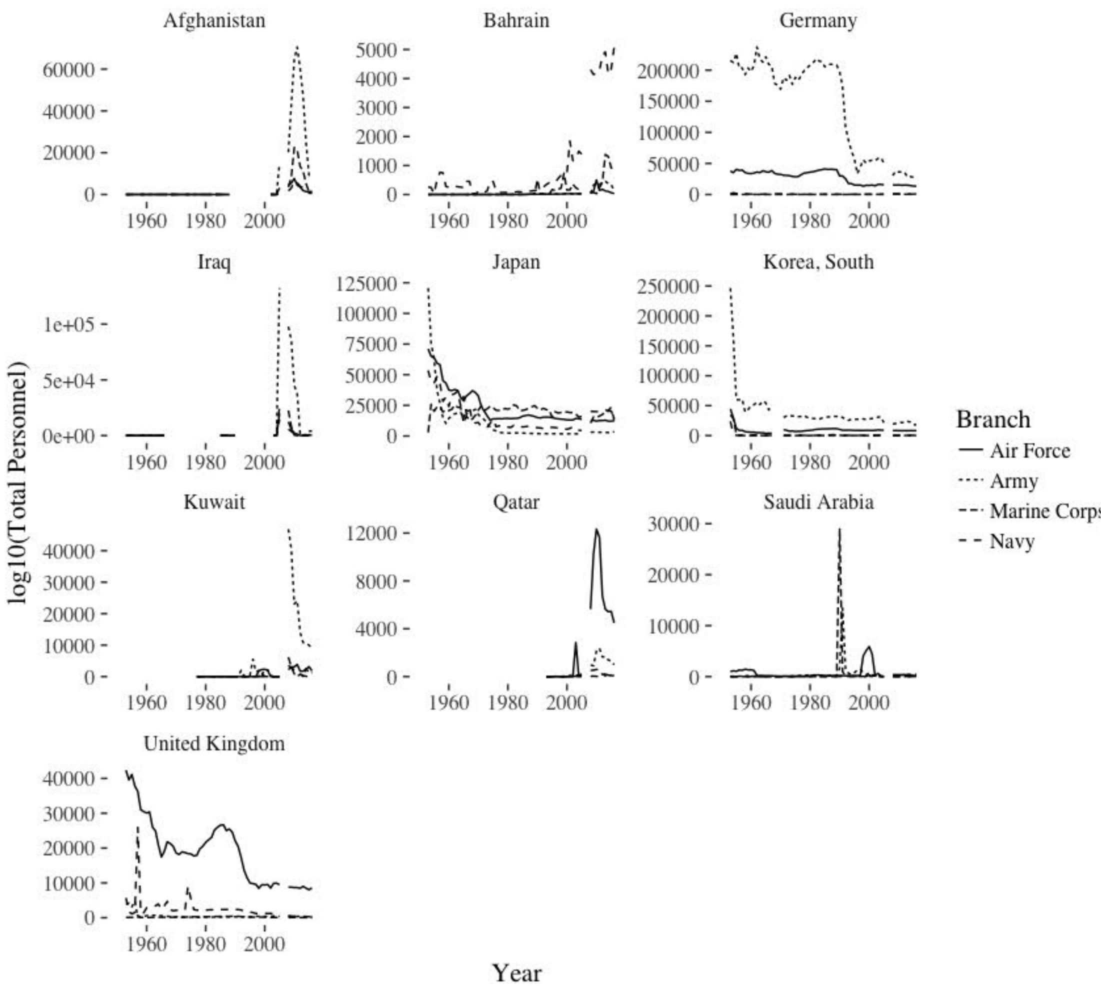


Figure 3: Troop Levels Abroad

Figure 3 also shows that certain countries are predominantly influenced by one particular service. For instance, the troop presence in Qatar is predominantly composed of Air Force personnel, whereas the troop level in Germany has historically been primarily Army personnel. We caveat that this trend has changed over time as other branches such as the Air Force have taken on a larger relative presence in Germany, compared to the Army.

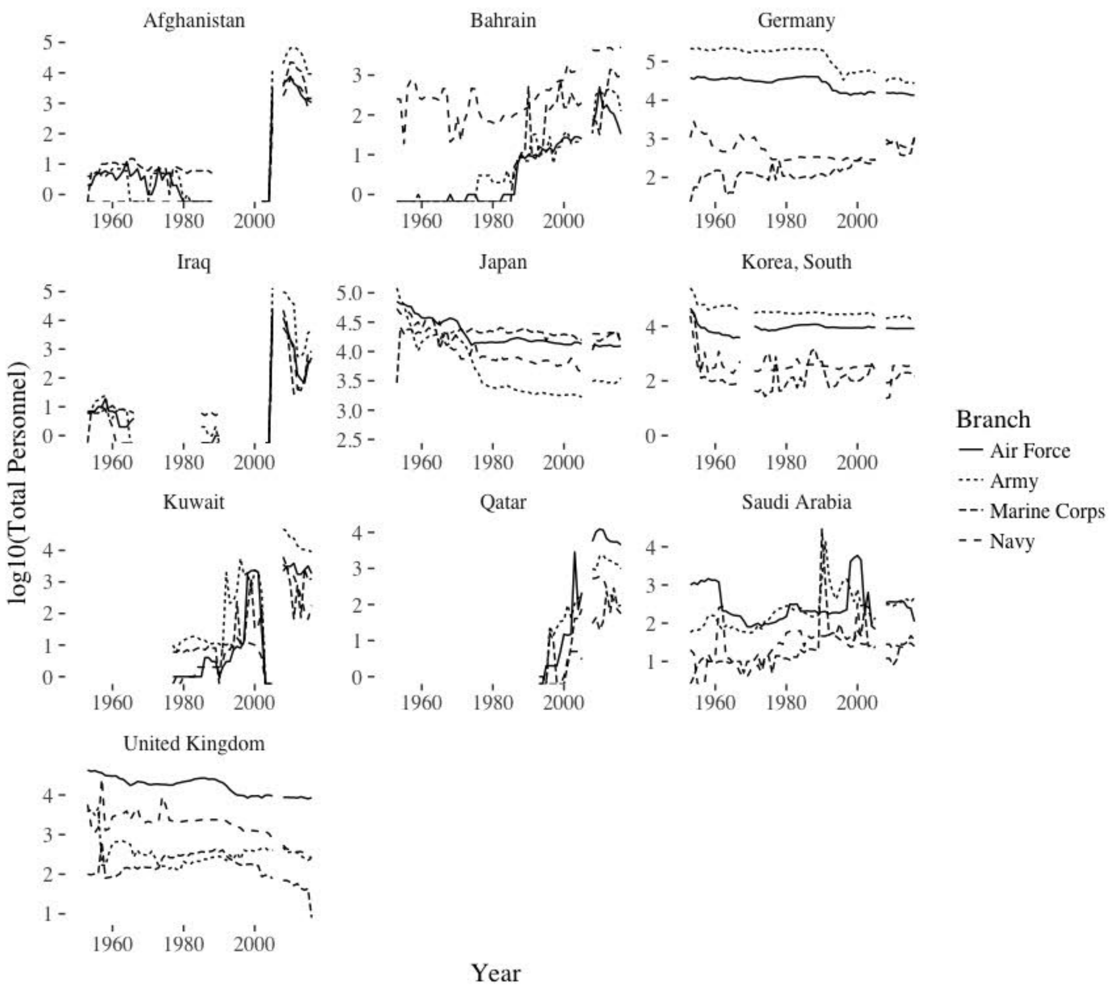


Figure 4: Logarithmic Transformation Applied to Troop Levels Abroad

Figure 4 shows the same data as in Figure 3, albeit with a logarithmic transformation applied to the number of personnel. The transformation better depicts the variance exhibited in the data. We can see that the United Kingdom, Germany, South Korea, and Japan have much smoother lines indicating less volatility in the number of troops present than do the other countries in Figure 4.

Data Selection for Model Training and Testing.

There is a desire by some forecasters to merely keep the most recent data because of the claim that, "the more recent data are most relevant to the current scenario." However, Hyndman [12] argues that, frequently, we do not have enough data to toss out observations. Hyndman's point is accurate with respect to the data available in this thesis. Each time series has at most 63 observations; one for each year from 1950-2016 with the years 1951, 1952, 2006, and 2007 missing from DMDC databases. While 2017 data is available at conclusion of this report, it was not available at the start of the project and was therefore not included in the models explained herein.

The traditional method for evaluating a forecast accuracy was provided in Section 2.8. The traditional method calls for partitioning the data such that 80 percent of the measurements are allocated towards training the model and 20 percent are allocated as testing points. This method was originally utilized for model evaluation; however, JDPAC is particularly interested in the forecast horizons of two and five years out. Therefore, the method of cross-validation, also referred to as rolling forecast origin, was utilized so as to repeatedly evaluate a model for its accuracy at the two and five year marks.

The traditional method divided the data such that the years 1950 through 2002 were classified as the training data while the years 2003 through 2016 were classified as the testing data. For the cross-validation evaluation, the same initial training data was utilized; however, as each year was subsequently evaluated, the training data moved forward by one year until only the final two and five years, respectively, were available for forecasting. The testing data set consequently decreased as the training data set increased.

3.2 Methodology

Country Name Variants.

Of note, the name of countries varied throughout the reporting period due to changes in data reporting methods as well as actual name changes. An interested reader is directed to the appendix for a full documentation of name changes made. The R code has been provided for this process for easy replication of the work.

Missing Data.

There was no clear cut rule on whether missing data should or should not be included when determining the length of the training and testing set when just a few missing data points exist. As mentioned in Section 3.1, the years 1951, 1952, 2006, and 2007 are missing for all countries in our forecast. While this troop data may appear in subsequent data collection efforts, it was not available for our forecasting, and the missing values were therefore interpolated. All missing data were linearly interpolated utilizing the nearest two non-missing data points. The entire data series was interpolated prior to separation into the training and test datasets. If a country was only reported for one year, the country was removed as interpolation could not be performed.

Data Frequency.

The frequency of data collection historically has been yearly; however, in recent years the reporting frequency has shifted towards a quarterly basis. For the purpose of this report, the annual reporting scheme has been utilized when developing forecasts. Should the frequency of data collection continue to include quarterly data, the recommended approach will be to account for this increased frequency of reporting. Moreover, the quarterly data will allow for seasonal decomposition.

Exogenous Variables.

To determine which exogenous variables might be worth considering for predicting troop strength levels, it was necessary first to determine which data were available. The number of datasets spanning from 1950 to present pertaining to exogenous variables that might improve the forecasting of military troop strengths were limited. Prior theses [25] from AFIT have compiled an assortment of data pertaining to political, military, economic, social, and infrastructure (PMESI) indicators for many countries. The indicators available vary depending on both the year and country. To overcome this limitation, we restricted the number of military troop strength observations to more recent data when constructing ARIMAX models so as to align with the availability of the PMESI indicators.

Exogenous variables were evaluated using the Granger Causality test which identifies whether the data series is a predictor for the other time series. That is, the Granger Causality Test determines whether or not a lag of one time series will be able to predict a change in another time series.

3.3 Testing Methodology

The primary tools utilized to construct and assess the relative forecasting models and their accuracy include native commands within **R**, as well as the *forecast* package for **R**, as developed by Hyndman and Khandakar [14]. The testing examined the following forecasting models: exponential smoothing, ARIMA, and ARIMAX.

Exponential Smoothing.

Exponential Smoothing Models were generated by varying the α-levels and predicting the next observation. Simple exponential smoothing models generally predict subsequent observations well because they give greater weight to more recent observations while still retaining values for past observations. While the simple exponential smoothing model does not account for the trend of the data and forecast the same value for the entire forecast horizon, the Holt exponential smoothing model can be utilized to account for the trend. Additionally, the **R** *forecast* package was utilized to automatically select the exponential state space model, and the selection criteria is documented in the paper by Hyndman et al. [16].

ARIMA.

A common obstacle for many people using ARIMA models for forecasting is that the "order selection process is usually considered subjective and difficult to apply" [14]. Fortunately, over the years attempts have been made to automate ARIMA modeling. Hyndman's *forecast* package in the **R** programming language provides a step-wise algorithm to forecast univariate time series with ARIMA, including selecting the parameters for the ARIMA model.

Regression with ARIMA Errors and ARIMAX.

Some forecasts are improved by utilizing exogenous variables to forecast data. The forecasts in this thesis looked at several variables available from the World Bank which were highlighted in work performed by Shallcross [25], who looked at several variables for conflict prediction. Shallcross utilized indicators to predict conflict, and those same predictors may also work to predict an increase in troop presence. This is because troop presence and conflict may be related. It is expected that, if a country is transitioning into conflict, the variables which predict its conflict will also be useful for predicting an increase in U.S. military troop levels for that country.

Forecasting Accuracy.

The two forecasts metrics utilized in this thesis are the Mean Absolute Error (MAE) and the Mean Absolute Scaled Error (MASE). Both are useful for different reasons. The MAE is useful when comparing forecast models for the same time period and the same time series. The MASE is useful to assess how accurate the model is compared to other models, even when the time series is different, because the errors are scaled to the values of the forecast series. For the conventional forecasting accuracy assessments, the MAE is used to compare forecast models to one another. For the cross-validation forecasting accuracy assessments, the MASE is used to compare models' forecasts over multiple years.

IV. Testing Results and Analysis

4.1 Direct Results by Country

The following sections in this Chapter provide the forecasting results for each country identified for study in Chapter 3. The following models presented were developed using Hyndman's [14] **R** *forecast* package: Simple Exponential Smoothing models with α ranging from 0.1 to 0.9 by increments of 0.2, exponential smoothing state space models generated utilizing the *ETS* function, ARIMA models generated utilizing the automatic ARIMA function, and Regression with ARIMA Errors model with Military Expenditures as a Percentage of GDP selected as the exogenous variable. Results are provided for the traditional and cross-validation methodologies.

Afghanistan.

Figure 5 shows the data for each service of the U.S. military for the country of Afghanistan. While the US military entered into Afghanistan in 2001 following the terrorist attacks against the US on September 11, 2001, DMDC did not provide personnel numbers for military personnel in Afghanistan until 2005.

Table 3 shows a comparison of the models with the traditional evaluation metric using the Mean Absolute Error. Unfortunately, the traditional evaluation metric does not produce impressive results, as the forecasts cannot predict the terrorist attack on September 11, 2001 which resulted in a large retaliation by the United States and subsequent deployment of many US military personnel to Afghanistan.

Figure 6 shows the forecast generated by the best performing model as determined by the model's Mean Absolute Error for the service having the highest number of military personnel present in Afghanistan. Most of the models were tied for accuracy for Afghanistan; therefore, the model with the lowest Mean Absolute Error was selected

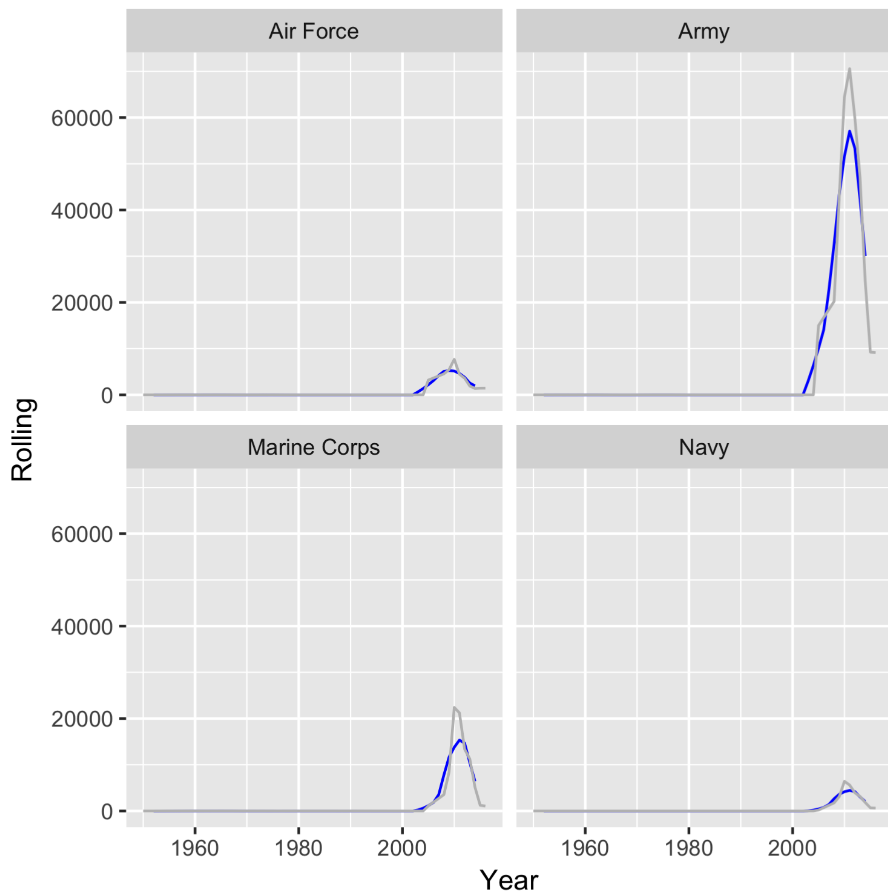


Figure 5: Afghanistan 5-Year Moving Average

which was a simple exponential smoothing with $\alpha = 0.1$. The Mean Absolute Error for this forecast is 28475.95, indicating that the model was off by 28,476 personnel each year. This indicates that the model had poor performance; however, this is to be expected, as the forecasts were trained primarily using data prior to the terrorist attacks on September 11, 2001 and tested on data subsequent to September 11, 2001.

Table 3: Afghanistan: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	3060.00	28476.21	6668.43	2090.50
2	Automatic ETS	3060.00	28476.21	6668.37	2090.50
3	Regression with ARIMA Errors	3054.56	28476.20	6659.56	2090.50
4	SES ($\alpha = 0.1$)	3059.78	28475.95	6666.44	2090.50
5	SES ($\alpha = 0.3$)	3060.00	28476.21	6667.83	2090.50
6	SES ($\alpha = 0.5$)	3060.00	28476.21	6668.17	2090.50
7	SES ($\alpha = 0.7$)	3060.00	28476.21	6668.32	2090.50
8	SES ($\alpha = 0.9$)	3060.00	28476.21	6668.40	2090.50

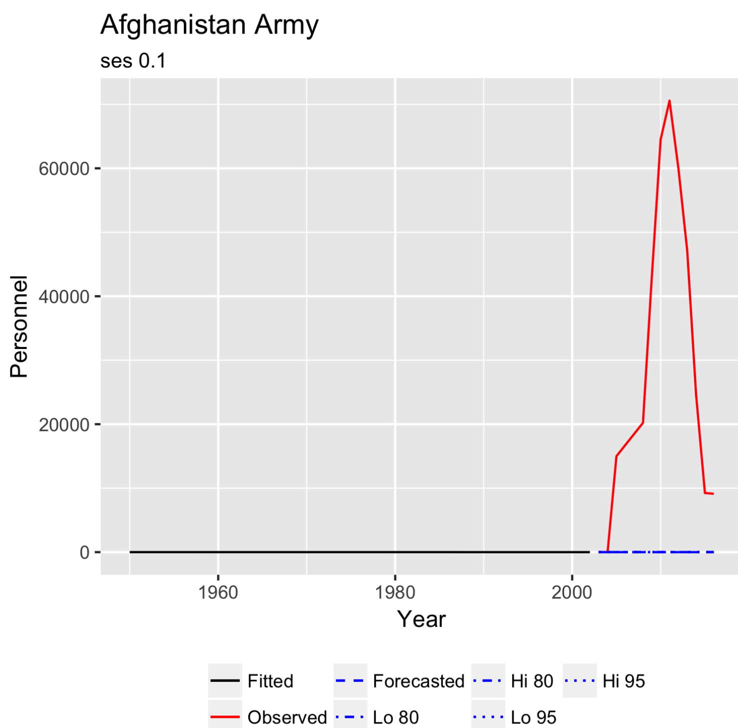


Figure 6: Afghanistan Best Performing Forecast

Utilizing the cross-validation accuracy assessment, the model which has the lowest Mean Absolute Scaled Error for the Army is the automatic ETS model with an Mean Absolute Scaled Error of 3347.79 when averaged over all years. The Mean Absolute Scaled Error allows for forecasts to be compared from one year to the next because there is not a dependency upon the size of the error. The lower the Mean Absolute Scaled Error, the better the model forecast accuracy. This large error is mostly due to the poor performance on years 2004-2005 and 2005-2006, which correspond to when DMDC updated their personnel numbers to reflect the War in Afghanistan.

Table 4 shows the average of the MASE for the cross-validation metrics. Only the best performing simple exponential smoothing model is provided. These values show the mean of the values from the plots shown in Figure 7. As mentioned previously, the MASE values are skewed due to the large inaccuracies for years 2004-2005 and 2005-2006; however, the model is much more accurate for all other forecast years.

The simple exponential smoothing model with $\alpha = 0.9$ performed the best, indicating that a forecast equivalent to the previous year's forecast may be sufficient to accurately predict subsequent years. Regression with ARIMA errors model was very consistent in its poor performance and was the worst of all models evaluated for Afghanistan. This may indicate that there is not a well-defined relationship between the number of personnel in Afghanistan and the military expenditures for Afghanistan as a percentage of its GDP.

Figure 7 shows the accuracies for models generated to forecast the number of Army personnel for Afghanistan. Only the best performing simple exponential smoothing model was provided for the sake of brevity. Moreover, only the Army, which had the highest number of personnel within the countr,y is shown due to the desire for brevity. With the exception of the years directly subsequent to the invasion of Afghanistan following September 11, 2001, the forecast accuracies were relatively equal.

Table 4: Afghanistan Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
2	Afghanistan	Air Force	ses_model($\alpha = 0.9$)	387.65
8	Afghanistan	Air Force	Automatic ETS	392.43
12	Afghanistan	Air Force	Automatic ARIMA	394.45
16	Afghanistan	Air Force	ARIMA_x_reg	397.67
5	Afghanistan	Army	Automatic ETS	3347.79
1	Afghanistan	Army	ses_model($\alpha = 0.9$)	3348.09
9	Afghanistan	Army	Automatic ARIMA	3353.09
13	Afghanistan	Army	ARIMA_x_reg	3357.86
3	Afghanistan	Marine Corps	ses_model($\alpha = 0.9$)	187.06
11	Afghanistan	Marine Corps	Automatic ARIMA	189.46
7	Afghanistan	Marine Corps	Automatic ETS	189.79
15	Afghanistan	Marine Corps	ARIMA_x_reg	204.32
6	Afghanistan	Navy	Automatic ETS	49.09
10	Afghanistan	Navy	Automatic ARIMA	54.64
4	Afghanistan	Navy	ses_model($\alpha = 0.9$)	56.27
14	Afghanistan	Navy	ARIMA_x_reg	86.07

Bahrain.

Figure 8 shows the five-year moving average for Bahrain. The Navy has the highest troop presence in Bahrain with nearly 5000 personnel present in 2016. The Marine Corps is second with approximately 1000 personnel present in 2016. The number of Air Force and Army personnel in the region is relatively insignificant compared to the other two services. The troop presence for the Air Force and Army appear to be mostly constant over the time period observed with neither service ever having more than 1000 personnel in the country at any given time. Conversely, the troop levels for Navy appear to be rising drastically. The Marine Corps is also showing signs of growth in the region, but not as notably as the Navy.

Table 5 shows the Mean Absolute Error for each model developed for the country of Bahrain using the traditional forecast evaluation with on 80/20 split for training and validation, respectively. The best performing model for the Air Force for Bahrain is the Regression with ARIMA Errors which is off by approximately 80 personnel each

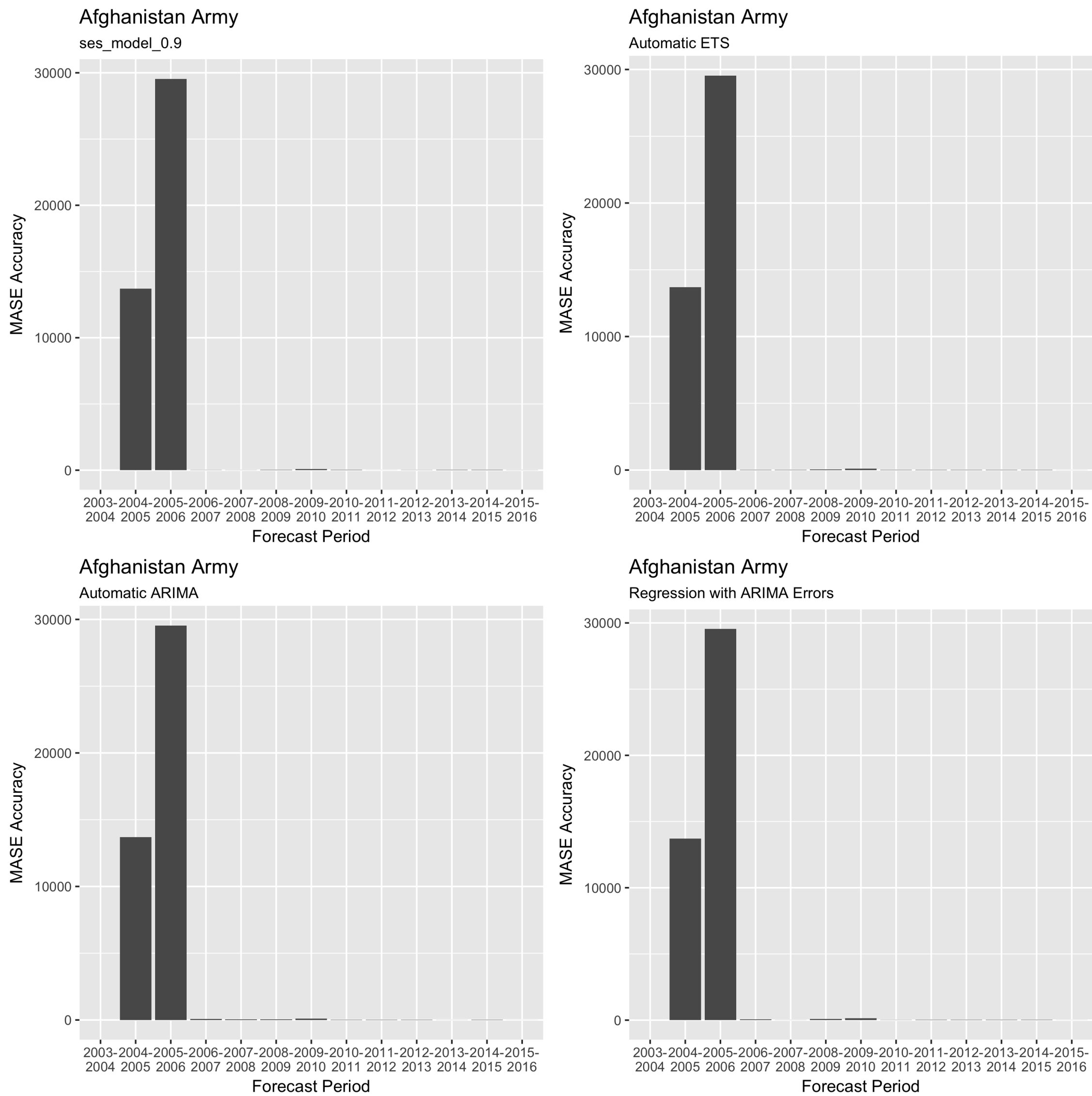


Figure 7: Afghanistan Cross-Validation Accuracies

year. The best performing Army model is that generated by the automatic exponential state space smoothing model, which was off by approximately 176 personnel each year. The best performing Marine Corps model was the simple exponential smoothing model with an α value of 0.1; the model was off by approximately three hundred personnel each year. The best performing model for the Navy was the exponential smoothing state space model which was off by approximately 1937.75 personnel each year over the 14-year forecast horizon.

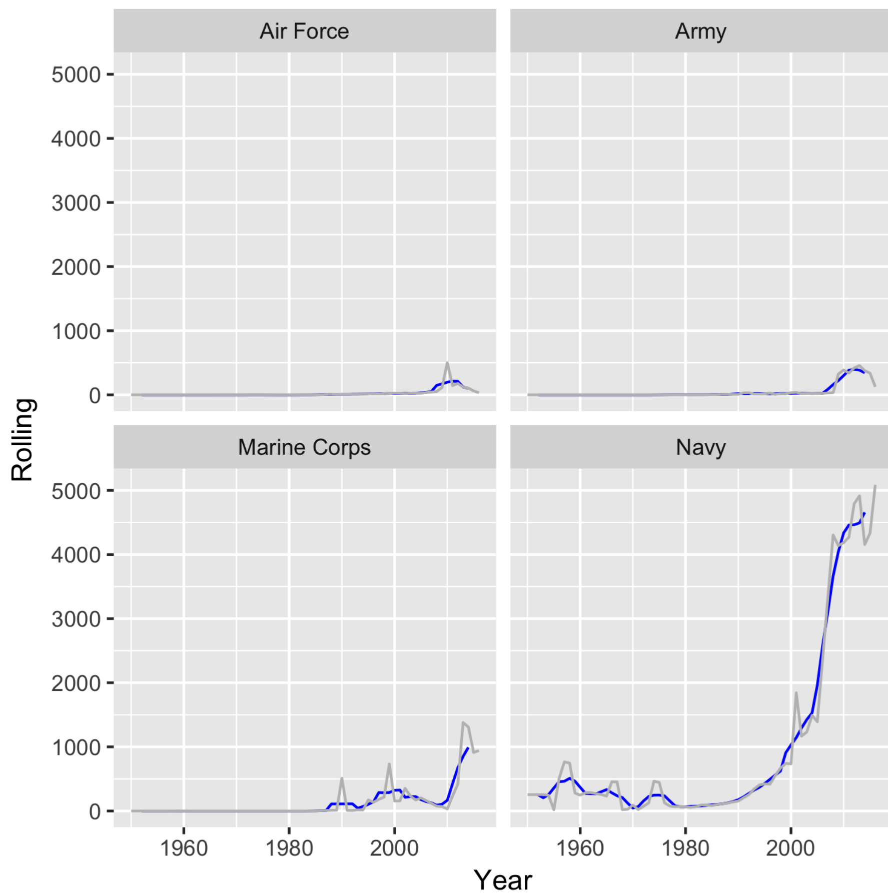


Figure 8: Bahrain 5-Year Moving Average

Figure 9 shows the forecast generated by the best performing model as determined by the model's Mean Absolute Error for the service with the highest number of military personnel present in Bahrain. The best model in this case was that generated utilizing the automatic ETS function. As Figure 9 shows, the forecast generated is not able to well predict the surge in Navy personnel which occurs between 2000 and 2010.

Table 5: Bahrain: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	79.83	186.56	336.03	2309.91
2	Automatic ETS	82.83	176.01	351.84	1937.75
3	Regression with ARIMA Errors	79.72	181.69	348.94	2758.60
4	SES ($\alpha = 0.1$)	90.89	191.74	332.75	2971.61
5	SES ($\alpha = 0.3$)	83.29	185.96	340.01	2532.61
6	SES ($\alpha = 0.5$)	81.60	185.26	345.39	2353.36
7	SES ($\alpha = 0.7$)	81.70	185.92	349.09	2307.57
8	SES ($\alpha = 0.9$)	82.51	187.64	357.26	2348.25

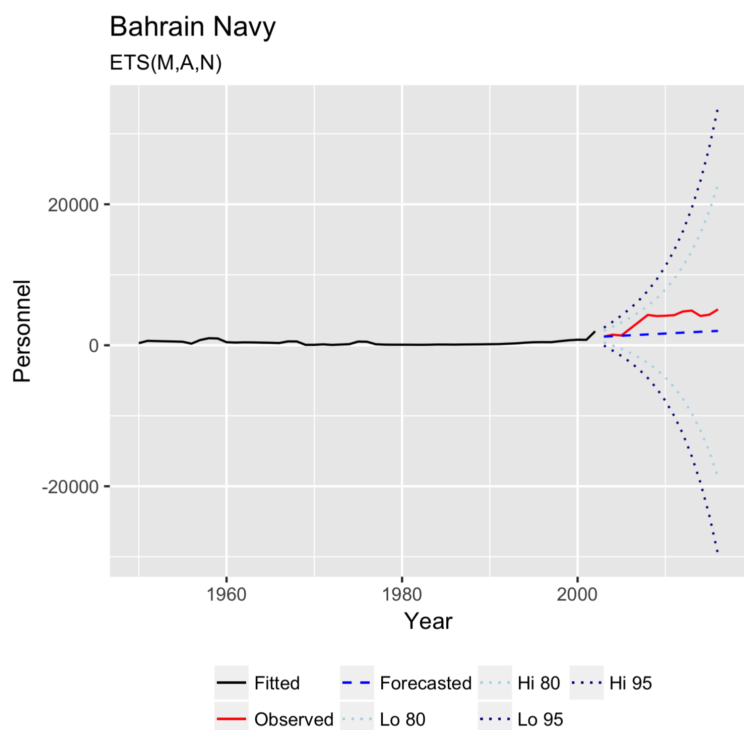


Figure 9: Bahrain Best Performing Forecast

Table 6 shows the cross-validation accuracy for the country of Bahrain. The table shows that, for the Navy, the best performing model was generated utilizing the automatic ETS function, which was also the case with the traditional forecast evaluation. For the Air Force, Army, and Marine Corps, the best models were the simple exponential smoothing models with $\alpha = 0.9$.

Table 6: Bahrain Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Bahrain	Air Force	ses_model_0.9	27.52
2	Bahrain	Air Force	Automatic ETS	32.57
3	Bahrain	Air Force	Automatic ARIMA	33.46
4	Bahrain	Air Force	ARIMA_x_reg	33.87
5	Bahrain	Army	ses_model_0.9	16.33
6	Bahrain	Army	Automatic ETS	16.59
7	Bahrain	Army	Automatic ARIMA	16.96
8	Bahrain	Army	ARIMA_x_reg	21.68
9	Bahrain	Marine Corps	ses_model_0.9	4.25
10	Bahrain	Marine Corps	ARIMA_x_reg	4.48
11	Bahrain	Marine Corps	Automatic ARIMA	4.87
12	Bahrain	Marine Corps	Automatic ETS	5.37
13	Bahrain	Navy	Automatic ETS	3.97
14	Bahrain	Navy	ses_model_0.9	4.28
15	Bahrain	Navy	Automatic ARIMA	4.71
16	Bahrain	Navy	ARIMA_x_reg	9.09

Germany.

Figure 10 shows a five-year moving average for each military service with forces present in Germany from 1950 to 2016. The number of Army personnel has historically been much greater than the presence of the other military services. There has been a sharp decrease in the number of personnel stationed in Germany since the end of the Cold War in 1990.

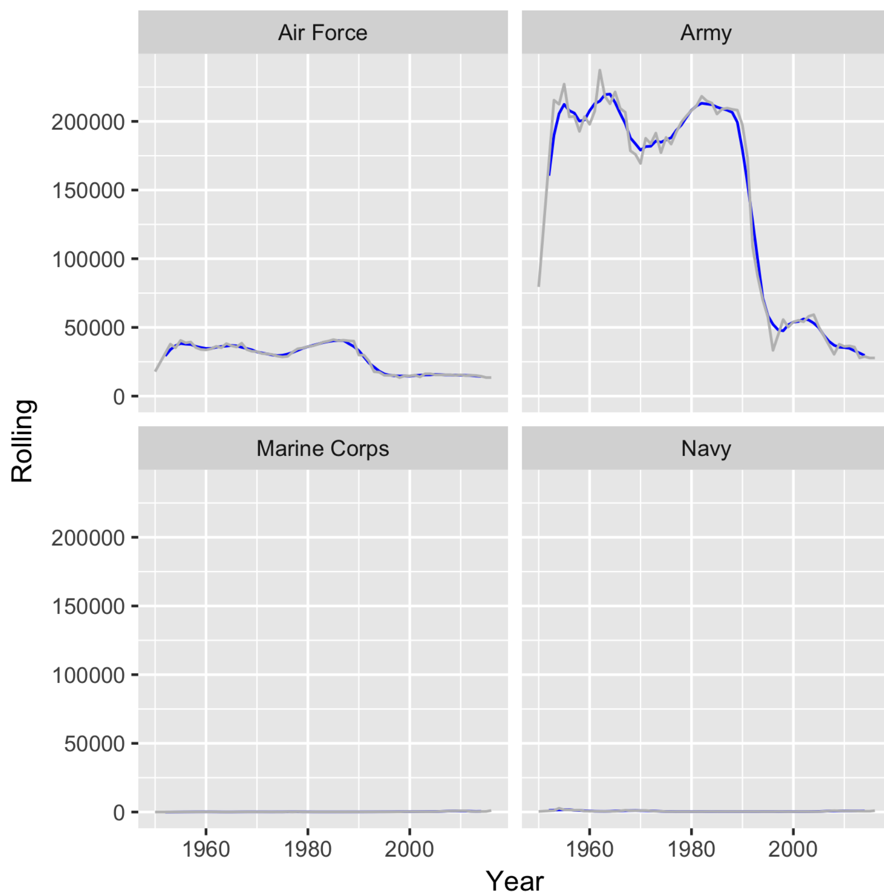


Figure 10: Germany 5-Year Moving Average

Table 7 shows the Mean Absolute Error for the forecast errors from 2003 to 2016. The worst performing model for the Air Force is the Regression with ARIMA errors which was off by approximately 9000 Air Force personnel each year and which is substantially worse than the best performing model, the simple exponential smoothing model with an $\alpha = 0.3$, which was off by only 600 personnel each year.

Table 7: Germany: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	3761.15	15359.04	293.78	328.43
2	Automatic ETS	1257.34	17065.64	295.47	343.78
3	Regression with ARIMA Errors	9299.71	28335.59	321.75	307.22
4	SES ($\alpha = 0.1$)	6796.45	63895.45	362.33	316.20
5	SES ($\alpha = 0.3$)	597.22	18982.53	307.22	333.92
6	SES ($\alpha = 0.5$)	912.22	16982.64	296.18	331.22
7	SES ($\alpha = 0.7$)	1027.58	17142.64	296.02	328.77
8	SES ($\alpha = 0.9$)	1171.81	17125.99	299.71	328.01

For the Army, the best performing model was generated utilizing the automatic ARIMA function from Hyndman's [14] **R** *forecast* package. The (p,d,q) values were (1,2,0), indicating an autoregressive order of 1 and a differencing of 2 with no moving average terms. This model's forecast is depicted in Figure 11.

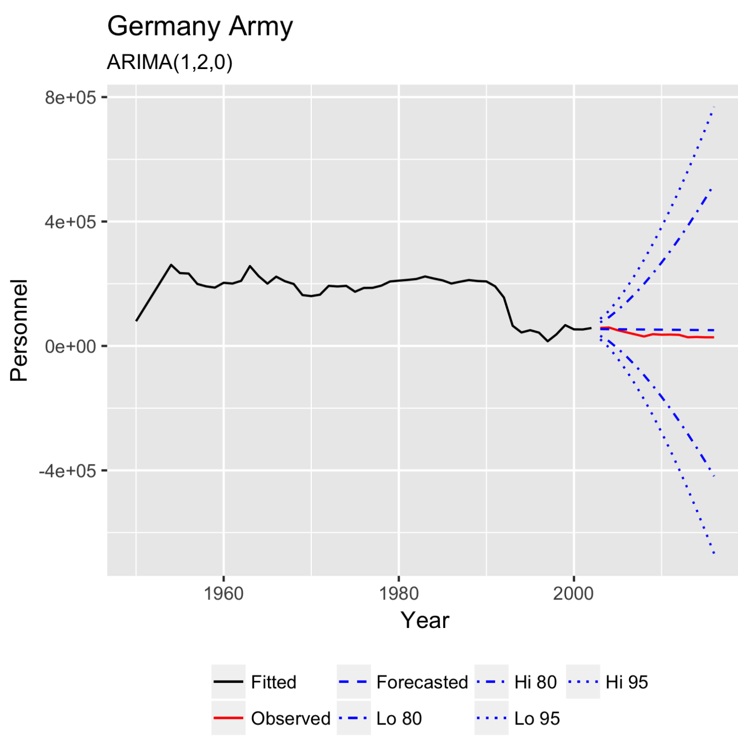


Figure 11: Germany Best Performing Forecast

Table 8 shows the cross-validation accuracy for the models developed for Germany. There was not a consistently best performing model which worked well for all services. The Air Force was forecasted most accurately utilizing a simple exponential smoothing model with $\alpha = 0.3$, while the Navy was best forecasted utilizing a regression with ARIMA errors model.

Table 8: Germany Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Germany	Air Force	ses_model_0.3	0.28
2	Germany	Air Force	Automatic ETS	0.30
3	Germany	Air Force	Automatic ARIMA	0.38
4	Germany	Air Force	ARIMA_x_reg	0.72
5	Germany	Army	ses_model_0.9	0.43
6	Germany	Army	Automatic ETS	0.44
7	Germany	Army	Automatic ARIMA	0.54
8	Germany	Army	ARIMA_x_reg	0.73
9	Germany	Marine Corps	Automatic ARIMA	4.67
10	Germany	Marine Corps	ses_model_0.9	4.99
11	Germany	Marine Corps	Automatic ETS	5.55
12	Germany	Marine Corps	ARIMA_x_reg	5.65
13	Germany	Navy	ARIMA_x_reg	0.95
14	Germany	Navy	Automatic ARIMA	0.96
15	Germany	Navy	ses_model_0.9	0.99
16	Germany	Navy	Automatic ETS	1.07

Iraq.

Figure 12 shows by service the number of military personnel in Iraq. The Army has the highest number of personnel present in the country. The number of military personnel was fairly low until the 2003 Invasion of Iraq when the United States ousted Saddam Hussein.

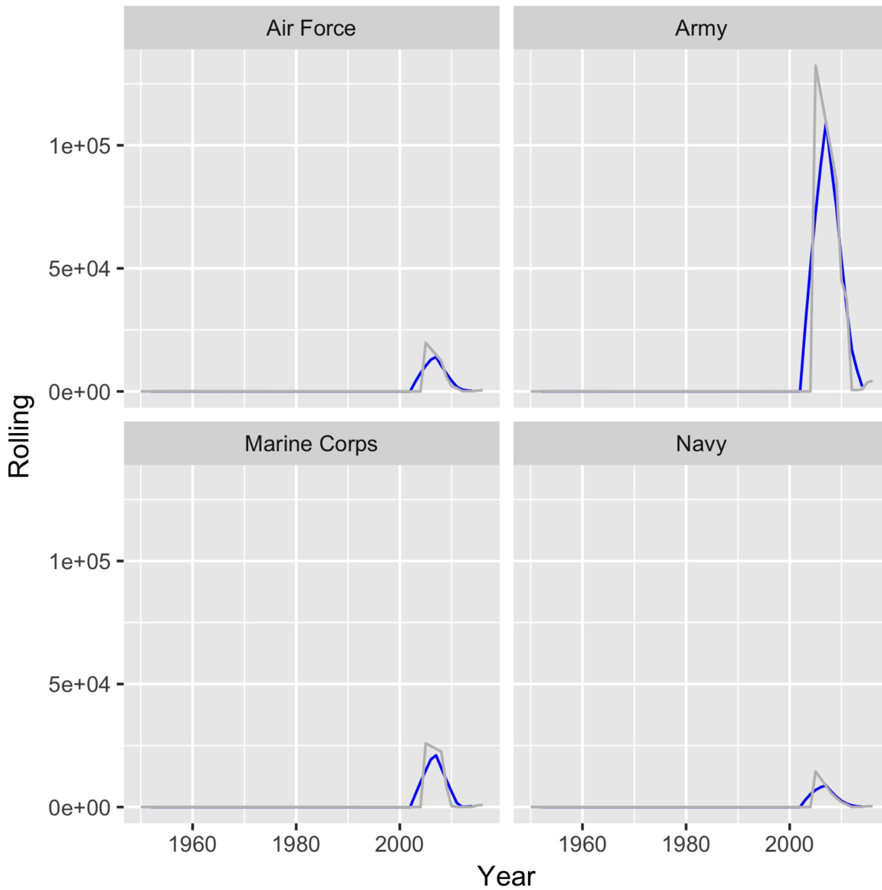


Figure 12: Iraq 5-Year Moving Average

Table 9 shows the forecast accuracy when utilizing the traditional evaluation method. The best performing model for the Army was the simple exponential smoothing model with $\alpha = 0.1$; however, all of the models failed to perform well due to the training data being collected prior to the 2003 Invasion of Iraq. The Mean Absolute Error was 45,602 personnel each year for the Army.

Table 9: Iraq: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	5337.00	45602.00	7658.14	3430.43
2	Automatic ETS	5337.00	45602.00	7658.09	3430.43
3	Regression with ARIMA Errors	5337.00	45602.09	7658.10	3430.43
4	SES ($\alpha = 0.1$)	5336.72	45600.95	7657.09	3430.38
5	SES ($\alpha = 0.3$)	5336.99	45601.35	7658.08	3430.43
6	SES ($\alpha = 0.5$)	5337.00	45601.70	7658.07	3430.43
7	SES ($\alpha = 0.7$)	5337.00	45601.91	7658.07	3430.43
8	SES ($\alpha = 0.9$)	5337.00	45601.99	7658.11	3430.43

Figure 13 shows the best performing forecast model for Army personnel in Iraq. The Army represent the largest military presence within the country. As shown, the forecast fails to well predict the 2003 Invasion in Iraq and as a result the number forecast errors are quite high. The red line indicates that the observed values differs sharply from the dashed lines, which represent the forecasted values. The dotted lines showing the confidence intervals are not distinguishable from the dashed blue line due to the poor scaling as a result of the large observed values. The observed values fall entirely outside the confidence intervals indicating a poor prediction accuracy.

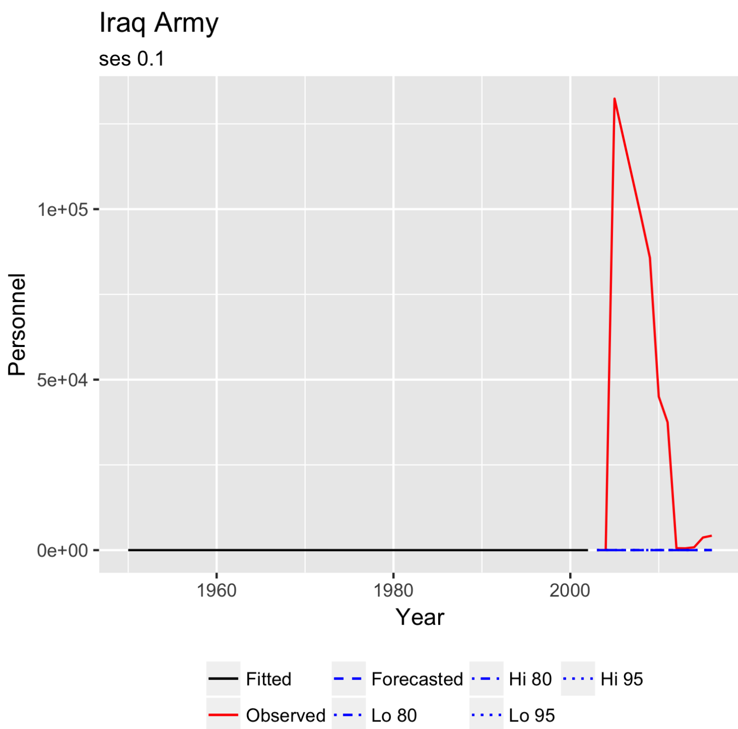


Figure 13: Iraq Best Performing Forecast

Table 10 shows the forecast errors utilizing the cross-validation methodology. The best performing model was the simple exponential smoothing for three out of four services with the Navy being the exception, which was best predicted by the model generated utilizing the automatic exponential state space smoothing algorithm. The Mean Absolute Scaled Error was quite high due to the 2003 invasion of Iraq; however, other years were relatively well-forecasted. Iraq forecasts share similar characteristics to those of Afghanistan in that both countries experienced large and dramatic increases as the US military invaded each country.

Table 10: Iraq Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Iraq	Air Force	ses_model_0.9	2801.91
2	Iraq	Air Force	Automatic ETS	2802.76
3	Iraq	Air Force	ARIMA_x_reg	2804.33
4	Iraq	Air Force	Automatic ARIMA	2806.54
5	Iraq	Army	ses_model_0.9	12249.07
6	Iraq	Army	ARIMA_x_reg	12252.28
7	Iraq	Army	Automatic ETS	12252.41
8	Iraq	Army	Automatic ARIMA	12254.77
9	Iraq	Marine Corps	ses_model_0.9	4521.98
10	Iraq	Marine Corps	Automatic ETS	4525.49
11	Iraq	Marine Corps	ARIMA_x_reg	4527.80
12	Iraq	Marine Corps	Automatic ARIMA	4528.81
13	Iraq	Navy	Automatic ETS	6978.90
14	Iraq	Navy	ses_model_0.9	6979.06
15	Iraq	Navy	ARIMA_x_reg	6979.32
16	Iraq	Navy	Automatic ARIMA	6981.51

Japan.

Figure 14 shows the observed values along with a five-year moving average for military personnel in Japan. In the early 1950s until the 1960s, the Army had the highest number of military personnel, but currently the Marine Corps has the largest military presence within the country. The number of military personnel for the Army, Air Force, and Marine Corps has remained fairly constant since around 1975. The Navy has increased its presence in Japan since the start of the 21st century.

Table 11 shows the traditional forecast accuracy for military personnel present in Japan with the Mean Absolute Error provided for each service. The automatic ETS function performed best for the Air Force, the simple exponential smoothing with $\alpha = 0.1$ performed best for the Army, the regression with ARIMA errors performed best for both the Marine Corps and the Navy.

Figure 15 illustrates the best model based upon prediction accuracy for the Marine Corps. The model is the regression with ARIMA (1,0,0) errors indicating that the

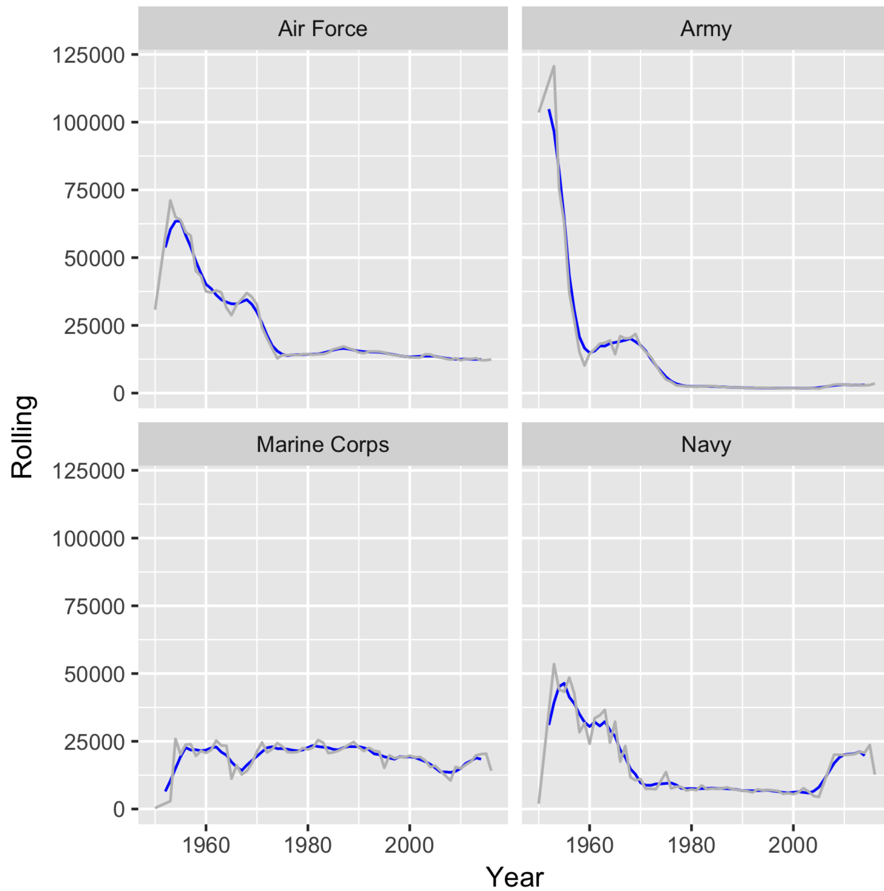


Figure 14: Japan 5-Year Moving Average

errors are dependent upon the immediately preceding error and there is no differencing required and a moving average term is not utilized.

Table 11: Japan: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	733.74	851.48	3525.00	8994.43
2	Automatic ETS	641.87	890.22	3520.01	9285.45
3	Regression with ARIMA Errors	1066.09	551.25	3434.84	8918.92
4	SES ($\alpha = 0.1$)	2378.80	495.36	4152.34	9143.11
5	SES ($\alpha = 0.3$)	857.79	901.34	3570.35	9625.82
6	SES ($\alpha = 0.5$)	698.90	902.84	3527.98	9479.58
7	SES ($\alpha = 0.7$)	653.08	897.18	3522.62	9278.83
8	SES ($\alpha = 0.9$)	642.96	892.10	3519.93	9083.16

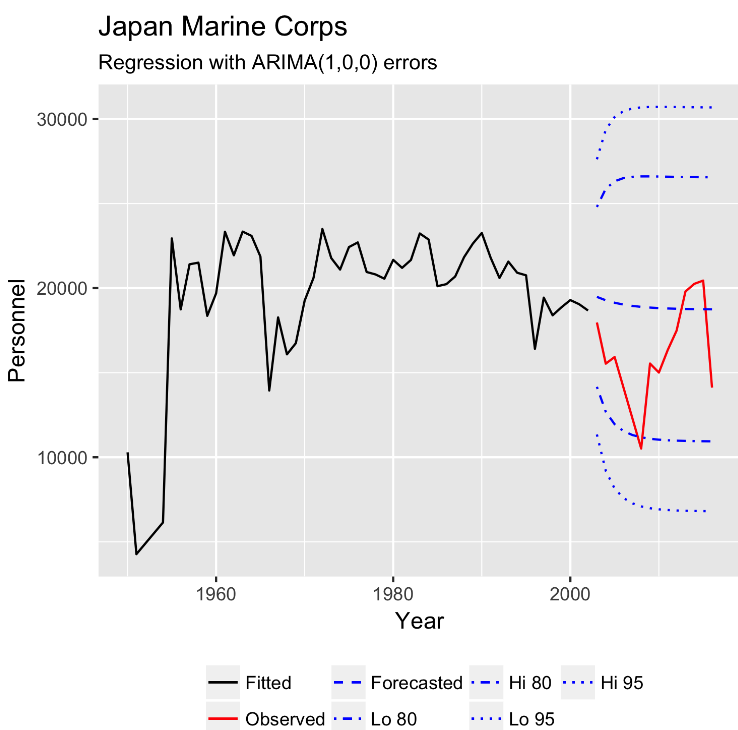


Figure 15: Japan Best Performing Forecast

Table 12 shows the cross-validation results on the Mean Absolute Scaled Error for Japan. All of the MASE values are relatively low indicating that each model has predicted the future values quite well. There appears to be less dramatic fluctuation in the number of military personnel present for Japan than the other selected countries.

This is due in part to the enduring presence of US military since the end of World War II. The best performing model for the Marines, which have the largest personnel presence in Japan was the ARIMA model.

Table 12: Japan Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Japan	Air Force	ses_model_0.5	0.22
2	Japan	Air Force	Automatic ETS	0.22
3	Japan	Air Force	Automatic ARIMA	0.29
4	Japan	Air Force	ARIMA_x_reg	0.30
5	Japan	Army	Automatic ETS	0.09
6	Japan	Army	ses_model_0.9	0.09
7	Japan	Army	Automatic ARIMA	0.10
8	Japan	Army	ARIMA_x_reg	0.12
9	Japan	Marine Corps	Automatic ARIMA	0.95
10	Japan	Marine Corps	ses_model_0.9	0.99
11	Japan	Marine Corps	ARIMA_x_reg	1.00
12	Japan	Marine Corps	Automatic ETS	1.05
13	Japan	Navy	ARIMA_x_reg	0.77
14	Japan	Navy	Automatic ARIMA	0.77
15	Japan	Navy	ses_model_0.9	0.80
16	Japan	Navy	Automatic ETS	0.86

Kuwait.

Figure 16 shows the observed values of military personnel for each military service in Kuwait. The Army has the largest troop presence in the country. As with other Middle Eastern countries, there is a visible, sudden increase in the number of military personnel present in the country since the start of the War on Terror in September 2001. There has been a fairly sharp decline in the number of military personnel present in the country since around 2008.

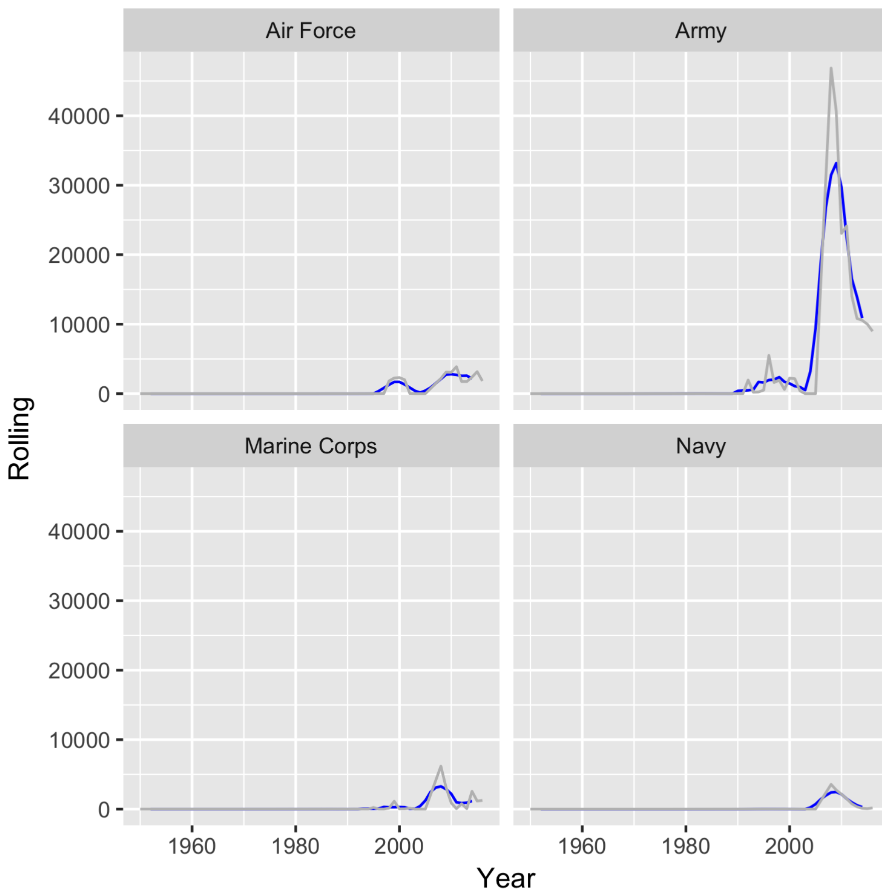


Figure 16: Kuwait 5-Year Moving Average

Table 13 shows the traditional forecast accuracy for troop personnel in Kuwait. The best performing model for the Army, Air Force, Marine Corps and Navy are the simple exponential smoothing model with $\alpha = 0.3$, Regression with ARIMA errors, Regression with ARIMA errors, and simple exponential smoothing model with $\alpha =$ 0.3.

Table 13: Kuwait: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	1886.31	16035.97	1610.67	1067.21
2	Automatic ETS	1791.60	16036.87	1528.61	1067.21
3	Regression with ARIMA Errors	1791.71	16027.85	1500.82	1067.22
4	SES ($\alpha = 0.1$)	1430.67	16231.66	1531.15	1065.50
5	SES ($\alpha = 0.3$)	1215.78	16045.32	1513.86	1064.97
6	SES ($\alpha = 0.5$)	1272.40	16174.35	1522.47	1065.83
7	SES ($\alpha = 0.7$)	1441.28	16337.94	1531.43	1066.53
8	SES ($\alpha = 0.9$)	1676.69	16524.05	1531.82	1067.03

Figure 17 shows the best performing forecast for the military service with the largest number of personnel present in Kuwait. The model in this instance is the Regression with ARIMA (0,1,1) errors, indicating the errors are forecasted using no autoregressive terms, one order of differencing, and one moving average term.

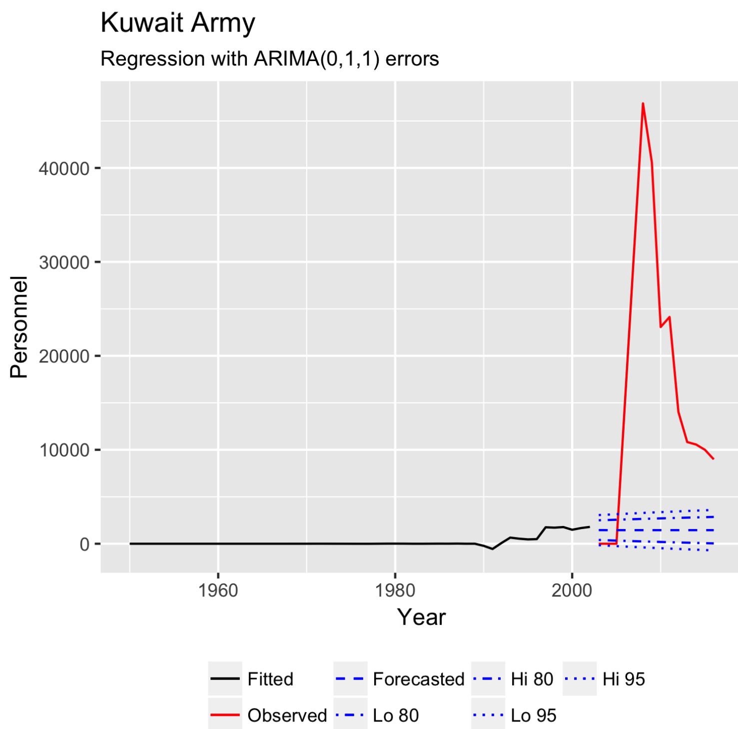


Figure 17: Kuwait Best Performing Forecast

Table 14 shows the cross-validation accuracy for forecasting military personnel present in Kuwait. The cross-validation accuracies are calculated utilizing two-year forecast horizons repeated from 2003 until 2016. The best performing model for the Air Force under this evaluation method is the Regression with ARIMA errors for the Air Force, and simple exponential smoothing with $\alpha = 0.9$ for the other three services.

Table 14: Kuwait Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Kuwait	Air Force	ARIMA_x_reg	6.56
2	Kuwait	Air Force	Automatic ARIMA	6.58
3	Kuwait	Air Force	Automatic ETS	6.59
4	Kuwait	Air Force	ses_model_0.9	6.94
5	Kuwait	Army	ses_model_0.9	14.93
6	Kuwait	Army	ARIMA_x_reg	17.55
7	Kuwait	Army	Automatic ARIMA	18.17
8	Kuwait	Army	Automatic ETS	18.18
9	Kuwait	Marine Corps	ses_model_0.9	14.40
10	Kuwait	Marine Corps	ARIMA_x_reg	17.33
11	Kuwait	Marine Corps	Automatic ETS	17.66
12	Kuwait	Marine Corps	Automatic ARIMA	20.08
13	Kuwait	Navy	ses_model_0.9	263.66
14	Kuwait	Navy	Automatic ETS	267.81
15	Kuwait	Navy	Automatic ARIMA	269.59
16	Kuwait	Navy	ARIMA_x_reg	274.52

Qatar.

Figure 18 shows the number of military personnel present in Qatar broken down by service from 1950 through 2016. The blue line indicates a five-year moving average which is helpful for identifying sizable variations in the number of military personnel for a particular year. For instance, we note that the grey line representing the observed value is much higher than the five-year moving average in 2010, as there was a sizable increase in military personnel that year. The service with the largest number of military personnel present in Qatar is the Air Force with approximately 5,000 personnel as of 2016; however, we observe that there is a sharp downward trend in the number of personnel present in the country since 2010. The Army, Marine Corps, and Navy do not have a sizable presence within the country.

Table 15 shows the forecast accuracy for our suite of models for each service. All models for the Air Force performed poorly due to failing to account for the sharp, sudden increase in military personnel present in the country following the start of

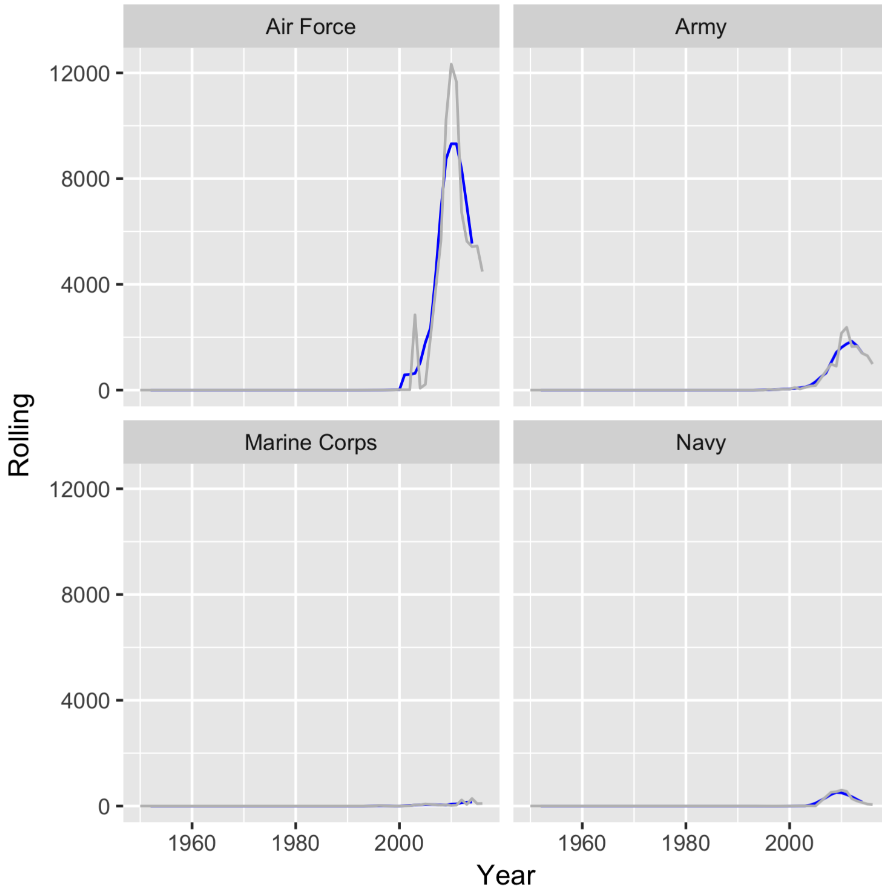


Figure 18: Qatar 5-Year Moving Average

the Global War on Terror. The other services did not experience a sizable increase in personnel stationed in Qatar and, as a result, their forecasts follow the observed values more closely.

Figure 19 shows the best performing forecast for Air Force personnel present in Qatar. The model is an ARIMA(2,2,2) model generated utilizing the automatic ARIMA function provided by Hyndman's [14] **R** *forecast* package.

Table 15: Qatar: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	5415.40	928.44	79.30	246.39
2	Automatic ETS	5453.93	902.21	79.13	231.09
3	Regression with ARIMA Errors	5453.83	928.75	74.95	247.49
4	SES ($\alpha = 0.1$)	5464.14	1048.24	79.68	247.79
5	SES ($\alpha = 0.3$)	5458.40	1024.82	78.41	246.74
6	SES ($\alpha = 0.5$)	5455.62	1016.42	77.72	245.75
7	SES ($\alpha = 0.7$)	5454.43	1016.18	76.65	245.05
8	SES ($\alpha = 0.9$)	5454.03	1021.74	75.52	244.55

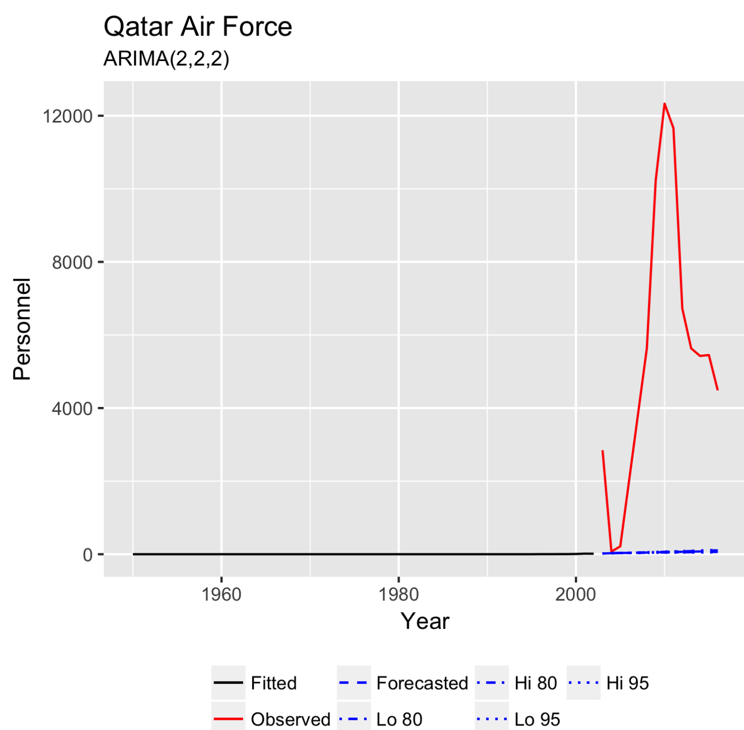


Figure 19: Qatar Best Performing Forecast

Table 16 shows the cross-validation accuracy for models generated for each service in Qatar. The best performing model was again the automatic ARIMA model; however, all models performed approximately the same.

Table 16: Qatar Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Qatar	Air Force	Automatic ARIMA	353.34
2	Qatar	Air Force	ARIMA_x_reg	354.45
3	Qatar	Air Force	ses_model_0.9	355.42
4	Qatar	Air Force	Automatic ETS	358.23
5	Qatar	Army	Automatic ETS	24.25
6	Qatar	Army	Automatic ARIMA	26.35
7	Qatar	Army	ses_model_0.9	26.43
8	Qatar	Army	ARIMA_x_reg	27.84
9	Qatar	Marine Corps	ARIMA_x_reg	17.49
10	Qatar	Marine Corps	ses_model_0.9	17.56
11	Qatar	Marine Corps	Automatic ETS	18.25
12	Qatar	Marine Corps	Automatic ARIMA	18.69
13	Qatar	Navy	ses_model_0.9	212.74
14	Qatar	Navy	Automatic ETS	217.22
15	Qatar	Navy	Automatic ARIMA	221.16
16	Qatar	Navy	ARIMA_x_reg	225.47

Saudi Arabia.

Figure 20 shows the number of military personnel present in Saudi Arabia broken down by service. The United States military sent in large numbers of military personnel during the Gulf War in 1990. Other than during that time period the number of military personnel in the country appears relatively small.

Table 17 shows the forecast accuracy utilizing the Mean Absolute Error by performing the traditional 80/20 accuracy assessment method. The best performing model for the Air Force, Army, and Navy were the simple exponential smoothing models with $\alpha = 0.9$. The Marine Corps was best forecasted utilizing the automatic ARIMA forecasting function.

Figure 21 shows the forecast accuracy for the service with the greatest number of military personnel present in the country since 2003.

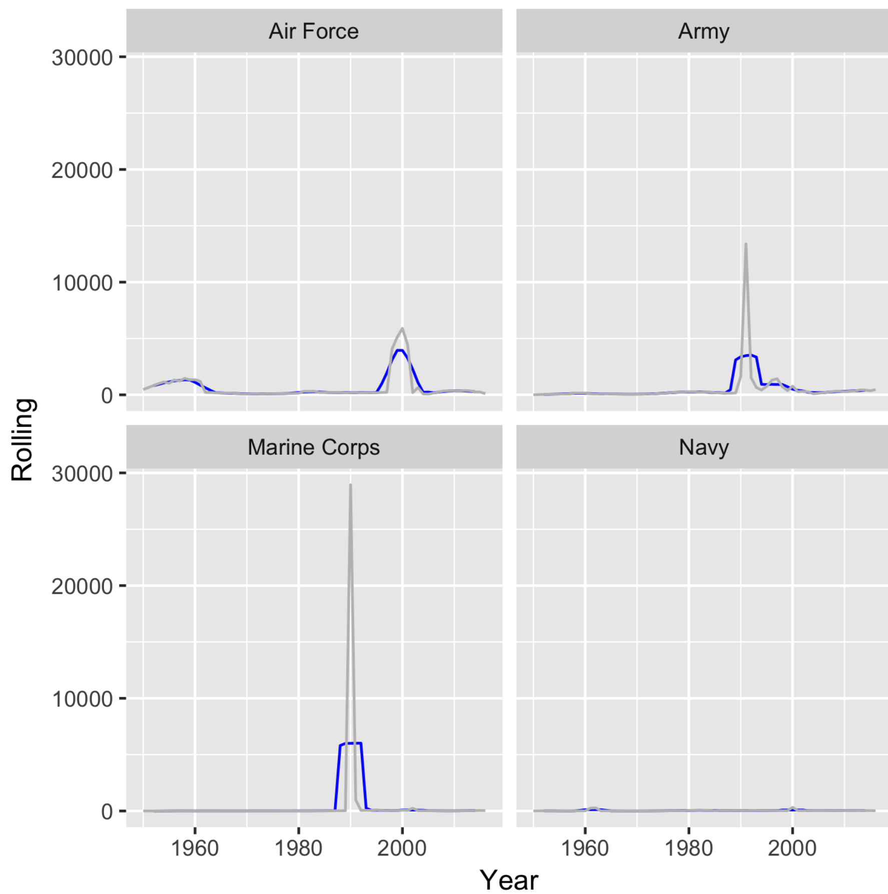


Figure 20: Saudi Arabia 5-Year Moving Average

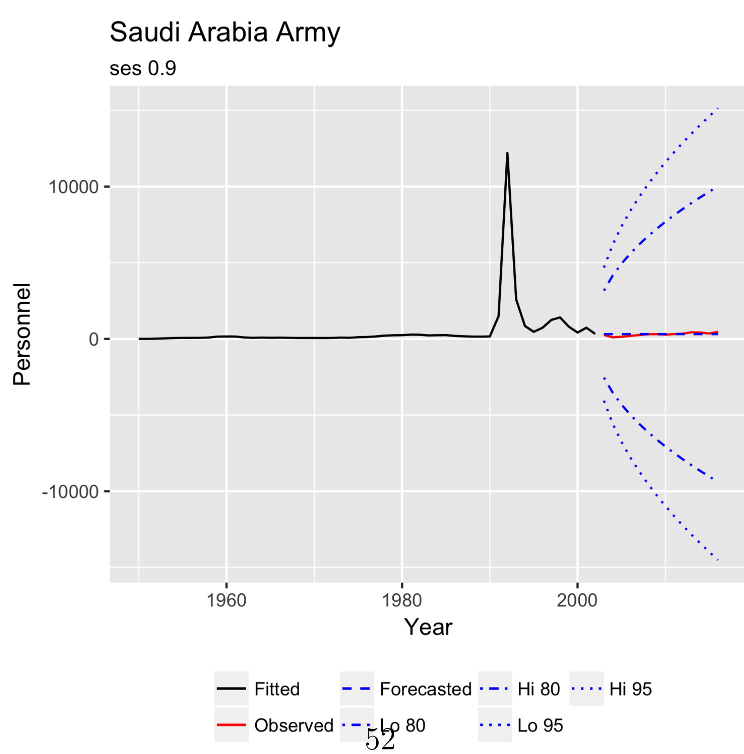


Figure 21: Saudi Arabia Best Performing Forecast

Table 17: Saudi Arabia: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	1625.20	240.80	23.36	14.44
2	Automatic ETS	2524.68	601.43	563.43	14.07
3	Regression with ARIMA Errors	1587.64	173.51	562.06	7.73
4	SES ($\alpha = 0.1$)	1378.47	693.03	882.86	33.23
5	SES ($\alpha = 0.3$)	2427.89	311.72	208.38	46.98
6	SES ($\alpha = 0.5$)	2114.97	124.35	124.63	39.37
7	SES ($\alpha = 0.7$)	1277.80	86.86	158.81	20.99
8	SES ($\alpha = 0.9$)	350.46	79.33	196.58	4.90

Table 18 shows the cross-validation accuracy for the models generated to predict the number of US military personnel present in Saudi Arabia. For all services, the best performing model was the simple exponential smoothing model with $\alpha = 0.9$.

Table 18: Saudi Arabia Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Saudi Arabia	Air Force	ses_model_0.9	0.44
2	Saudi Arabia	Air Force	Automatic ETS	0.93
3	Saudi Arabia	Air Force	ARIMA_x_reg	1.53
4	Saudi Arabia	Air Force	Automatic ARIMA	2.00
5	Saudi Arabia	Army	ses_model_0.9	0.13
6	Saudi Arabia	Army	ARIMA_x_reg	0.23
7	Saudi Arabia	Army	Automatic ARIMA	0.37
8	Saudi Arabia	Army	Automatic ETS	0.54
9	Saudi Arabia	Marine Corps	ses_model_0.9	0.02
10	Saudi Arabia	Marine Corps	Automatic ARIMA	0.02
11	Saudi Arabia	Marine Corps	ARIMA_x_reg	0.45
12	Saudi Arabia	Marine Corps	Automatic ETS	0.47
13	Saudi Arabia	Navy	ses_model_0.9	0.14
14	Saudi Arabia	Navy	ARIMA_x_reg	0.14
15	Saudi Arabia	Navy	Automatic ARIMA	0.47
16	Saudi Arabia	Navy	Automatic ETS	0.53

South Korea.

Figure 22 shows a centered five-year moving average for South Korea. The service with the highest number of troops in South Korea is the Army with approximately 25,000 personnel in the country each year since the 1970s. Looking at Figure 22, we note that the other military services have a relatively minor troop presence in comparison to the Army.

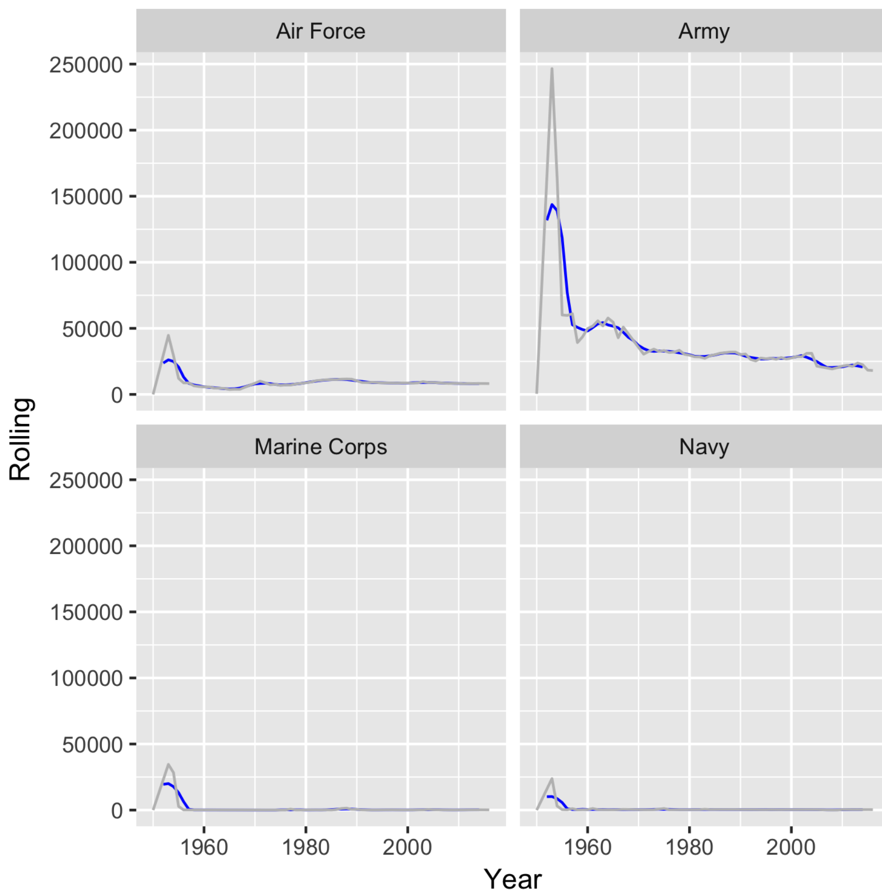


Figure 22: South Korea 5-Year Moving Average

Table 19 shows the forecast accuracy utilizing the Mean Absolute Error and the traditional 80/20 accuracy method. The best performing model for the Army was the simple exponential smoothing model with an $\alpha = 0.3$. The Air Force, Marine Corps were best forecasted utilizing the simple exponential smoothing model with $\alpha = 0.3$, the automatic ARIMA model, respectively. The Navy tied between the automatic ARIMA model, the automatic ETS model, and the simple exponential smoothing models with $\alpha =$ either 0.7 or 0.9. The worst performing model for all services was the regression with ARIMA errors model which had a forecast error nearly 200% higher than the forecast error of the best performing model when forecasting Army personnel.

Table 19: South Korea: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	814.33	8118.75	53.50	79.14
2	Automatic ETS	471.20	8419.55	55.79	79.14
3	Regression with ARIMA Errors	629.60	12645.42	931.30	473.86
4	SES ($\alpha = 0.1$)	620.16	7694.19	120.65	99.73
5	SES ($\alpha = 0.3$)	412.71	6648.90	62.11	81.50
6	SES ($\alpha = 0.5$)	397.39	6847.08	61.91	79.92
7	SES ($\alpha = 0.7$)	404.70	6987.13	58.48	79.14
8	SES ($\alpha = 0.9$)	417.12	7044.00	56.30	79.14

Figure 23 shows the best performing model for the service with the highest number of personnel present in the South Korea. The model and service in this case were the simple exponential smoothing model with $\alpha = 0.3$ and Army, respectively.

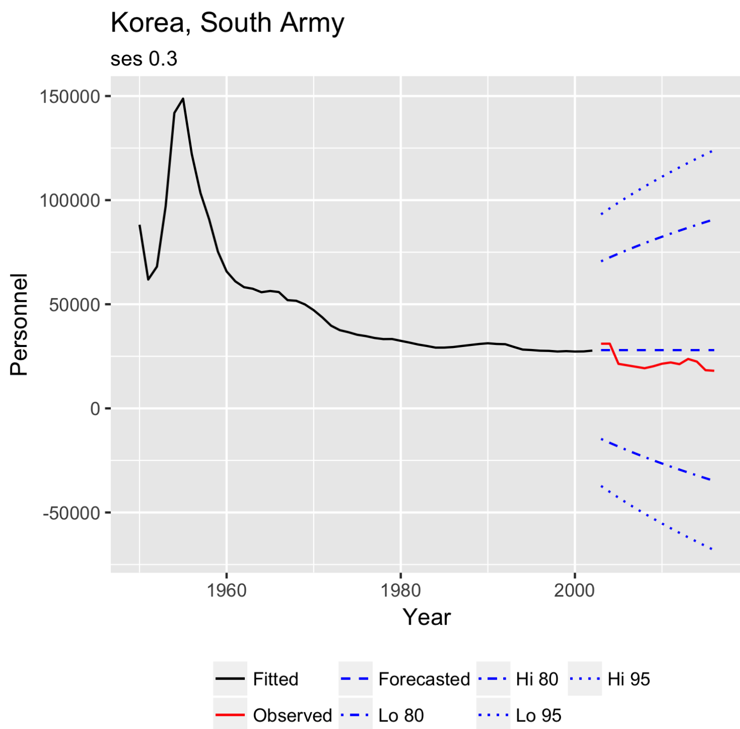


Figure 23: South Korea Best Performing Forecast

Table 20 shows the cross-validation accuracy for South Korea. The best performing model when forecasting the number of Army personnel present in South Korea was the simple exponential smoothing model with $\alpha = 0.9$. This differs from the model obtained utilizing the traditional forecasting evaluation where previously the model with $\alpha = 0.3$ performed most accurately. The best performing models for the Air Force and Marine Corps were the automatic ETS models; however, they were nearly tied by the simple exponential smoothing models with $\alpha = 0.9$. The Navy was equally well predicted utilizing either the automatic ARIMA model or the simple exponential smoothing model with $\alpha = 0.9$.

Table 20: South Korea Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	Korea, South	Air Force	Automatic ETS	0.10
2	Korea, South	Air Force	ses_model_0.9	0.11
3	Korea, South	Air Force	ARIMA_x_reg	0.21
4	Korea, South	Air Force	Automatic ARIMA	0.30
5	Korea, South	Army	ses_model_0.9	0.27
6	Korea, South	Army	Automatic ETS	0.29
7	Korea, South	Army	Automatic ARIMA	0.47
8	Korea, South	Army	ARIMA_x_reg	0.55
9	Korea, South	Marine Corps	Automatic ETS	0.05
10	Korea, South	Marine Corps	ses_model_0.9	0.05
11	Korea, South	Marine Corps	Automatic ARIMA	0.08
12	Korea, South	Marine Corps	ARIMA_x_reg	0.41
13	Korea, South	Navy	Automatic ARIMA	0.09
14	Korea, South	Navy	ses_model_0.9	0.09
15	Korea, South	Navy	Automatic ETS	0.11
16	Korea, South	Navy	ARIMA_x_reg	0.33

United Kingdom.

Figure 24 shows the five-year moving average for all military services in the United Kingdom. Historically, the service with the highest number of troops has been the Air Force. The number of troops present in the United Kingdom has stayed relatively constant since the early 21st Century, with the Air Force maintaining around 10,000 troops and all other services maintaining troop levels near zero.

Table 21 shows the accuracy for the models evaluated to forecast the United Kingdom utilizing the traditional evaluation rule of 80% of the data to train and 20% to test. The best performing model for the Air Force was the simple exponential smoothing model with α =0.7. The best performing models for the Army, Marine Corps, and Navy were the simple exponential smoothing with α =0.3, the Marine Corps with $\alpha = 0.9$, and Navy with the automatic ETS model.

Figure 25 shows the simple exponential smoothing model with $\alpha = 0.7$. The red line indicating the observed values mirrors very closely with the dashed blue

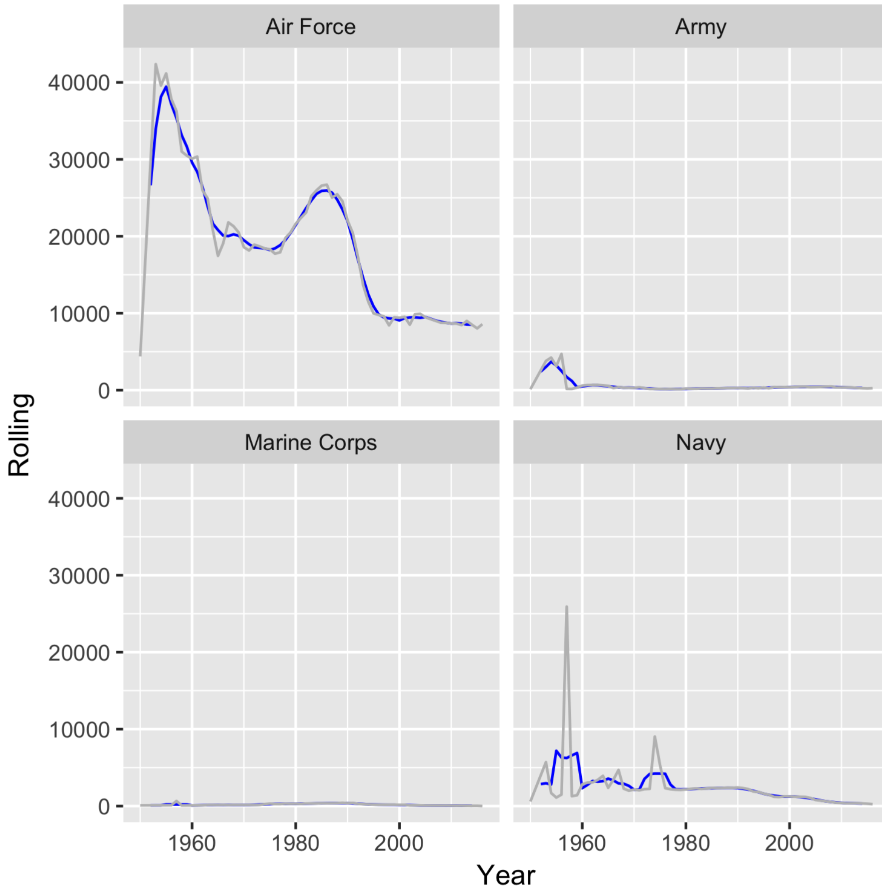


Figure 24: United Kingdom 5-Year Moving Average

line representing the observed values. The dotted blue lines show the 80% and 95% confidence levels for the forecast. The forecast is off by an average of 400 personnel each year.

Table 22 shows the cross-validation accuracy for forecasts of US military troops present in the United Kingdom. The best performing model for the Air Force was the simple exponential smoothing model with an $\alpha = 0.7$ which is also the same as the model forecasted utilizing the traditional forecast accuracy metrics. The Army, Marine Corps, and Navy utilized the simple exponential smoothing models or the exponential state space smoothing models. The simple exponential smoothing model predicted 937.5% more accurately than the ARIMA model developed for the Navy.

Table 21: United Kingdom: Traditional Validation Method Using Mean Absolute Error for Evaluation

	Basic_Model	Air Force	Army	Marine Corps	Navy
1	Automatic ARIMA	2373.78	94.19	79.87	2323.36
2	Automatic ETS	5078.63	98.55	81.43	111.60
3	Regression with ARIMA Errors	3205.64	161.74	156.88	306.38
4	SES ($\alpha = 0.1$)	5237.89	69.97	159.89	1220.42
5	SES ($\alpha = 0.3$)	732.56	70.49	91.46	737.29
6	SES ($\alpha = 0.5$)	434.61	79.95	66.68	673.18
7	SES ($\alpha = 0.7$)	407.81	86.05	49.44	663.10
8	SES ($\alpha = 0.9$)	437.96	91.76	33.48	659.66

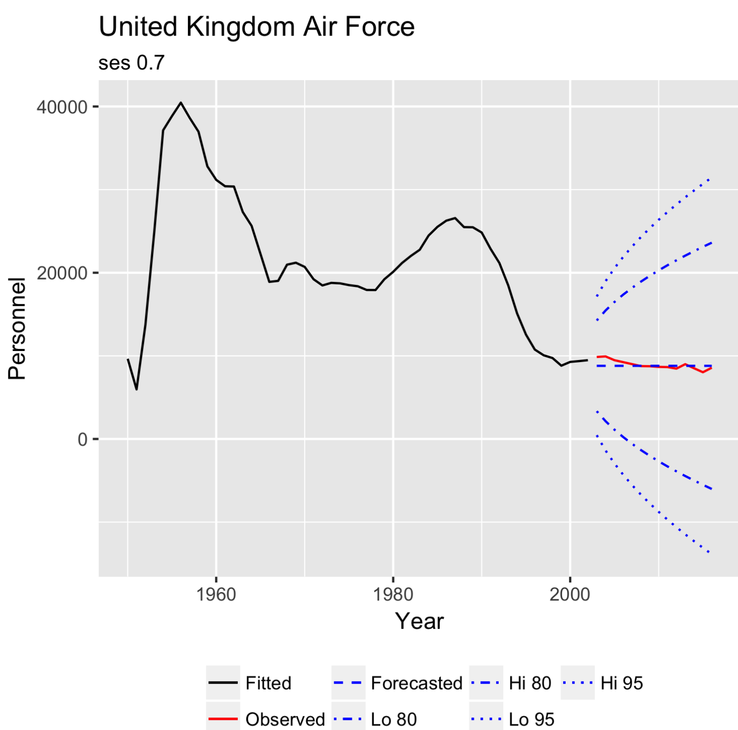


Figure 25: United Kingdom Best Performing Forecast

Table 22: United Kingdom Average Cross-Validation Accuracy

	Country	Service	Model	Average MASE
1	United Kingdom	Air Force	ses_model_0.7	0.20
2	United Kingdom	Air Force	Automatic ETS	0.24
3	United Kingdom	Air Force	ARIMA_x_reg	0.35
4	United Kingdom	Air Force	Automatic ARIMA	0.37
5	United Kingdom	Army	Automatic ETS	0.19
6	United Kingdom	Army	ses_model_0.9	0.19
7	United Kingdom	Army	Automatic ARIMA	0.19
8	United Kingdom	Army	ARIMA_x_reg	0.27
9	United Kingdom	Marine Corps	ses_model_0.9	0.22
10	United Kingdom	Marine Corps	ARIMA_x_reg	0.47
11	United Kingdom	Marine Corps	Automatic ETS	0.49
12	United Kingdom	Marine Corps	Automatic ARIMA	0.54
13	United Kingdom	Navy	ses_model_0.9	0.08
14	United Kingdom	Navy	Automatic ETS	0.08
15	United Kingdom	Navy	ARIMA_x_reg	0.55
16	United Kingdom	Navy	Automatic ARIMA	0.75

V. Conclusions and Recommendations

5.1 Quantitative Summary

This section provides discussion regarding the models developed for the countries of interest: Afghanistan, Bahrain, Germany, Iraq, Japan, Kuwait, Qatar, Saudi Arabia, South Korea, and the United Kingdom. The advantages and disadvantages of each model will be discussed as well as a recommended model for each country and branch. A generalized forecasting model will be suggested which consistently performs adequately for all countries and branches and can be used for simplified forecasting.

Model Comparisons.

There was no forecast model that consistently performed the best in all instances; however, the simple exponential smoothing model where $\alpha = 0.9$ appeared frequently in both the traditional forecast evaluation as well as the cross-validation evaluation. The regression with ARIMA errors models as well as the ARIMA models performed adequately in some instances, but each performed much worse in other instances and thus may not be a reliable set of models to depend upon when predicting troop strength. The models generated utilizing the automatic ETS models appear to perform adequately for many of the branches and countries and do not exhibit the extreme errors present within the ARIMA models.

Insights Derived.

The utilization of automatic forecasting tools contained within Hyndman's forecast package enable rapid, automatic, and potentially accurate forecasting which is necessary for organizations needing to make many predictions on multiple time series.

There is not always enough time to study each time series in depth, and the algorithms developed by Hyndman et al. [14] provide an adequate solution to a difficult problem. In the age of ever increasing data, the smart application of automation will enable costs savings and improved business forecasting.

For the countries analyzed, the Army was consistently best predicted utilizing a Simple Exponential Smoothing model or the Exponential State Space model function. The ARIMA and the Regression with ARIMA errors models did not outperform the Simple Exponential Smoothing model or the Exponential State Space model function for any of the selected countries in this research. This insight would lead a future forecaster to utilize exponential smoothing models when forecasting the Army's troop strength and to forgo utilizing the ARIMA or Regression with ARIMA errors models.

5.2 Recommendations for Future Research

Data Accuracy.

The accuracy of forecasts' outputs are dependent upon the accuracy of forecasts' inputs. Recent news stories [18, 26] have shown that the data accuracy provided by the Defense Manpower Data Center requires further scrutiny. In light of recent news stories, there has been some momentum to improve the troop personnel reporting accuracy. For instance, the Air Force is undergoing the process of updating its personnel systems [20] which may improve USTRANSCOM's ability to obtain accurate personnel counts for each country.

Recent news stories have discussed the Department of Defense's reporting of troop numbers in foreign countries. Reporting has shown that "previously disclosed troop numbers did not reflect the extent of the U.S. commitment on the ground since commanders sometimes brought in forces temporarily to get around the Obama-era limits" [1]. This effort to circumvent the capacities placed upon troop levels in certain countries has led to failure to accurately disclose troop numbers. Lt. Gen. Sean MacFarland recently justified this practice by stating, "It just didn't make sense to increase the Force Management Level when you were just bringing in some engineers for a little while to build a facility and then take them out" [21]. Other reasons for inaccurate reporting are due to military concerns regarding operational security [21].

Outlier Analysis.

It may be worthwhile for future researchers to investigate how well a forecast does on average while excluding years where it performs poorly. Utilizing the cross-validation technique, it could be observed that a particular data series has an irregularity in the data to such an extent that no models accurately predict the observation. As a result, averaging the MASE may not indicate how well the forecast typically performs. For instance, for Afghanistan, all of the forecasts perform very poorly for years 2004-2005 and 2005-2006 due to an inability to account for the surge in Troop Strength as a result of the Operation Enduring Freedom; however, if it is known and accepted that there will be some years where forecasts completely fail, then perhaps looking for models that consistently perform well and ignoring the years they perform horribly could result in more accurate overall forecasts. This strategy would likely work well for the Department of Defense whose budget will increase in the event that the military is tasked to send large numbers of personnel to a particular country, while also being good stewards of taxpayer dollars in ensuring that the TWCF aligns with anticipated demand.

Data Frequency.

The Defense Manpower Data Center has increased the frequency with which it reports data from annually to quarterly. This improved data reporting should be utilized to analyze each country for potential seasonal patterns as well as improved ability to forecast given additional data. The increased reporting frequency also allows for seasonal decomposition such that each element of the time series can be broken down to show the seasonal and trend component.

Incorporate Troop Forecasts when Predicting USTRANSCOM Workload.

According to information received by USTRANSCOM, the goal is to incorporate the global troop laydown into USTRANSCOM workload forecasting. This attempt at dynamic regression modeling may work to improve prediction accuracy.

Other Models.

There are many forecasting models available to utilize. The recent hype in data science is the utilization of artificial neural networks which were not explored in this thesis, but which may work well to forecast the data. With the exception of the Regression with ARIMA Errors, the models explored in this thesis are some of the basic models which are frequently utilized for forecasting.

Appendix A. Conventional Forecasting Accuracy Metrics

	Country	Branch	Model	Conventional MAE Accuracy	Conventional MASE Accuracy	Percent Imputed	Percent Off (MAE)	Percent Off (MASE)
1	Afghanistan	Air Force	Regression with ARIMA(1,0,0) errors	3054.56	2887.94	25.37	0.00	0.00
2	Afghanistan	Air Force	ses_model_0.1	3059.78	2892.88	25.37	0.17	0.17
3	Afghanistan	Air Force	ses_model_0.3	3060.00	2893.09	25.37	0.18	0.18
4	Afghanistan	Air Force	ETS(A,N,N)	3060.00	2893.09	25.37	0.18	0.18
5	Afghanistan	Air Force	ARIMA(0,1,1)	3060.00	2893.09	25.37	0.18	0.18
6	Afghanistan	Air Force	ses_model_0.5	3060.00	2893.09	25.37	0.18	0.18
7	Afghanistan	Air Force	ses_model_0.7	3060.00	2893.09	25.37	0.18	0.18
8	Afghanistan	Air Force	ses_model_0.9	3060.00	2893.09	25.37	0.18	0.18
9	Afghanistan	Army	ses_model_0.1	28475.95	51060.33	25.37	0.00	0.00
10	Afghanistan	Army	Regression with ARIMA(1,0,0) errors	28476.20	51060.78	25.37	0.00	0.00
11	Afghanistan	Army	ses_model_0.3	28476.21	51060.80	25.37	0.00	0.00
12	Afghanistan	Army	ses_model_0.5	28476.21	51060.80	25.37	0.00	0.00
13	Afghanistan	Army	ses_model_0.7	28476.21	51060.80	25.37	0.00	0.00
14	Afghanistan	Army	ETS(A,N,N)	28476.21	51060.80	25.37	0.00	0.00
15	Afghanistan	Army	ses_model_0.9	28476.21	51060.80	25.37	0.00	0.00
16	Afghanistan	Army	ARIMA(0,1,0)	28476.21	51060.80	25.37	0.00	0.00
17	Afghanistan	Marine Corps	Regression with ARIMA(1,0,0) errors	6659.56	5970.64	25.37	0.00	0.00

18	Afghanistan	Marine Corps	ses_model_0.1	6666.44	5976.81	25.37	0.10	0.10
19	Afghanistan	Marine Corps	ses_model_0.3	6667.83	5978.06	25.37	0.12	0.12
20	Afghanistan	Marine Corps	ses_model_0.5	6668.17	5978.36	25.37	0.13	0.13
21	Afghanistan	Marine Corps	ses_model_0.7	6668.32	5978.49	25.37	0.13	0.13
22	Afghanistan	Marine Corps	ETS(A,N,N)	6668.37	5978.54	25.37	0.13	0.13
23	Afghanistan	Marine Corps	ses_model_0.9	6668.40	5978.57	25.37	0.13	0.13
24	Afghanistan	Marine Corps	ARIMA(0,1,0)	6668.43	5978.59	25.37	0.13	0.13
25	Afghanistan	Navy	ETS(A,N,N)	2090.50		25.37	0.00	
26	Afghanistan	Navy	ses_model_0.1	2090.50		25.37	0.00	
27	Afghanistan	Navy	ses_model_0.3	2090.50		25.37	0.00	
28	Afghanistan	Navy	ses_model_0.5	2090.50		25.37	0.00	
29	Afghanistan	Navy	ses_model_0.7	2090.50		25.37	0.00	
30	Afghanistan	Navy	ses_model_0.9	2090.50		25.37	0.00	
31	Afghanistan	Navy	ARIMA(0,0,0) with non-zero mean	2090.50		25.37	0.00	
32	Afghanistan	Navy	ARIMA(0,0,0) with non-zero mean	2090.50		25.37	0.00	
33	Bahrain	Air Force	Regression with ARIMA(1,1,1) errors	79.72	76.76	7.46	0.00	0.00
34	Bahrain	Air Force	ARIMA(0,1,0) with drift	79.83	76.87	7.46	0.14	0.14
35	Bahrain	Air Force	ses_model_0.5	81.60	78.58	7.46	2.37	2.37
36	Bahrain	Air Force	ses_model_0.7	81.70	78.67	7.46	2.49	2.49
37	Bahrain	Air Force	ses_model_0.9	82.51	79.45	7.46	3.50	3.50
38	Bahrain	Air Force	ETS(A,N,N)	82.83	79.77	7.46	3.91	3.91
39	Bahrain	Air Force	ses_model_0.3	83.29	80.20	7.46	4.48	4.48
40	Bahrain	Air Force	ses_model_0.1	90.89	87.52	7.46	14.01	14.01

41	Bahrain	Army	ETS(A,A,N)	176.01	58.30	7.46	0.00	0.00
42	Bahrain	Army	Regression with ARIMA(3,1,2) errors	181.69	60.18	7.46	3.23	3.23
43	Bahrain	Army	ses_model_0.5	185.26	61.36	7.46	5.25	5.25
44	Bahrain	Army	ses_model_0.7	185.92	61.58	7.46	5.63	5.63
45	Bahrain	Army	ses_model_0.3	185.96	61.59	7.46	5.65	5.65
46	Bahrain	Army	ARIMA(3,1,0)	186.56	61.79	7.46	5.99	5.99
47	Bahrain	Army	ses_model_0.9	187.64	62.15	7.46	6.61	6.61
48	Bahrain	Army	ses_model_0.1	191.74	63.50	7.46	8.93	8.93
49	Bahrain	Marine Corps	ses_model_0.1	332.75	6.68	7.46	0.00	0.00
50	Bahrain	Marine Corps	ARIMA(0,1,1)	336.03	6.75	7.46	0.98	0.98
51	Bahrain	Marine Corps	ses_model_0.3	340.01	6.83	7.46	2.18	2.18
52	Bahrain	Marine Corps	ses_model_0.5	345.39	6.94	7.46	3.80	3.80
53	Bahrain	Marine Corps	Regression with ARIMA(0,1,1) errors	348.94	7.01	7.46	4.86	4.86
54	Bahrain	Marine Corps	ses_model_0.7	349.09	7.01	7.46	4.91	4.91
55	Bahrain	Marine Corps	ETS(A,A,N)	351.84	7.07	7.46	5.74	5.74
56	Bahrain	Marine Corps	ses_model_0.9	357.26	7.18	7.46	7.36	7.36
57	Bahrain	Navy	ETS(M,A,N)	1937.75	17.48	7.46	0.00	0.00
58	Bahrain	Navy	ses_model_0.7	2307.57	20.82	7.46	19.09	19.09
59	Bahrain	Navy	ARIMA(0,1,1)	2309.91	20.84	7.46	19.21	19.21
60	Bahrain	Navy	ses_model_0.9	2348.25	21.19	7.46	21.18	21.18
61	Bahrain	Navy	ses_model_0.5	2353.36	21.23	7.46	21.45	21.45
62	Bahrain	Navy	ses_model_0.3	2532.61	22.85	7.46	30.70	30.70
63	Bahrain	Navy	Regression with ARIMA(1,0,0) errors	2758.60	24.89	7.46	42.36	42.36
64	Bahrain	Navy	ses_model_0.1	2971.61	26.81	7.46	53.35	53.35

65	Germany	Air Force	ses_model_0.3	597.22	0.30	5.97	0.00	0.00
66	Germany	Air Force	ses_model_0.5	912.22	0.46	5.97	52.74	52.74
67	Germany	Air Force	ses_model_0.7	1027.58	0.52	5.97	72.06	72.06
68	Germany	Air Force	ses_model_0.9	1171.81	0.60	5.97	96.21	96.21
69	Germany	Air Force	ETS(A,N,N)	1257.34	0.64	5.97	110.53	110.53
70	Germany	Air Force	ARIMA(0,2,2)	3761.15	1.91	5.97	529.77	529.77
71	Germany	Air Force	ses_model_0.1	6796.45	3.45	5.97	1038.01	1038.01
72	Germany	Air Force	Regression with ARIMA(2,0,2) errors	9299.71	4.72	5.97	1457.16	1457.16
73	Germany	Army	ARIMA(1,2,0)	15359.04	1.23	5.97	0.00	0.00
74	Germany	Army	ses_model_0.5	16982.64	1.36	5.97	10.57	10.57
75	Germany	Army	ETS(A,N,N)	17065.64	1.36	5.97	11.11	11.11
76	Germany	Army	ses_model_0.9	17125.99	1.37	5.97	11.50	11.50
77	Germany	Army	ses_model_0.7	17142.64	1.37	5.97	11.61	11.61
78	Germany	Army	ses_model_0.3	18982.53	1.51	5.97	23.59	23.59
79	Germany	Army	Regression with ARIMA(2,0,2) errors	28335.59	2.26	5.97	84.49	84.49
80	Germany	Army	ses_model_0.1	63895.45	5.10	5.97	316.01	316.01
81	Germany	Marine Corps	ARIMA(1,1,0)	293.78	10.62	5.97	0.00	0.00
82	Germany	Marine Corps	ETS(A,N,N)	295.47	10.68	5.97	0.58	0.58
83	Germany	Marine Corps	ses_model_0.7	296.02	10.70	5.97	0.76	0.76
84	Germany	Marine Corps	ses_model_0.5	296.18	10.71	5.97	0.82	0.82
85	Germany	Marine Corps	ses_model_0.9	299.71	10.84	5.97	2.02	2.02
86	Germany	Marine Corps	ses_model_0.3	307.22	11.11	5.97	4.57	4.57
87	Germany	Marine Corps	Regression with ARIMA(1,0,2) errors	321.75	11.63	5.97	9.52	9.52
88	Germany	Marine Corps	ses_model_0.1	362.33	13.10	5.97	23.33	23.33

89	Germany	Navy	Regression with ARIMA(0,1,0) errors	307.22	2.21	5.97	0.00	0.00
90	Germany	Navy	ses_model_0.1	316.20	2.28	5.97	2.92	2.92
91	Germany	Navy	ses_model_0.9	328.01	2.36	5.97	6.77	6.77
92	Germany	Navy	ARIMA(0,1,0)	328.43	2.36	5.97	6.90	6.90
93	Germany	Navy	ses_model_0.7	328.77	2.37	5.97	7.01	7.01
94	Germany	Navy	ses_model_0.5	331.22	2.38	5.97	7.81	7.81
95	Germany	Navy	ses_model_0.3	333.92	2.40	5.97	8.69	8.69
96	Germany	Navy	ETS(M,A,N)	343.78	2.47	5.97	11.90	11.90
97	Iraq	Air Force	ses_model_0.1	5336.72	6607.37	46.27	0.00	0.00
98	Iraq	Air Force	ses_model_0.3	5336.99	6607.70	46.27	0.01	0.01
99	Iraq	Air Force	ses_model_0.5	5337.00	6607.71	46.27	0.01	0.01
100	Iraq	Air Force	ETS(A,N,N)	5337.00	6607.71	46.27	0.01	0.01
101	Iraq	Air Force	ses_model_0.7	5337.00	6607.71	46.27	0.01	0.01
102	Iraq	Air Force	ses_model_0.9	5337.00	6607.71	46.27	0.01	0.01
103	Iraq	Air Force	ARIMA(1,1,0)	5337.00	6607.71	46.27	0.01	0.01
104	Iraq	Air Force	Regression with ARIMA(1,1,0) errors	5337.00	6607.72	46.27	0.01	0.01
105	Iraq	Army	ses_model_0.1	45600.95	36480.76	46.27	0.00	0.00
106	Iraq	Army	ses_model_0.3	45601.35	36481.08	46.27	0.00	0.00
107	Iraq	Army	ses_model_0.5	45601.70	36481.36	46.27	0.00	0.00
108	Iraq	Army	ses_model_0.7	45601.91	36481.53	46.27	0.00	0.00
109	Iraq	Army	ses_model_0.9	45601.99	36481.59	46.27	0.00	0.00
110	Iraq	Army	ETS(A,N,N)	45602.00	36481.60	46.27	0.00	0.00
111	Iraq	Army	ARIMA(0,1,0)	45602.00	36481.60	46.27	0.00	0.00
112	Iraq	Army	Regression with ARIMA(0,1,0) errors	45602.09	36481.67	46.27	0.00	0.00

113	Iraq	Marine Corps	ses_model_0.1	7657.09	11541.12	46.27	0.00	0.00
114	Iraq	Marine Corps	ses_model_0.7	7658.07	11542.59	46.27	0.01	0.01
115	Iraq	Marine Corps	ses_model_0.5	7658.07	11542.59	46.27	0.01	0.01
116	Iraq	Marine Corps	ses_model_0.3	7658.08	11542.61	46.27	0.01	0.01
117	Iraq	Marine Corps	ETS(A,N,N)	7658.09	11542.63	46.27	0.01	0.01
118	Iraq	Marine Corps	Regression with ARIMA(0,1,0) errors	7658.10	11542.65	46.27	0.01	0.01
119	Iraq	Marine Corps	ses_model_0.9	7658.11	11542.66	46.27	0.01	0.01
120	Iraq	Marine Corps	ARIMA(0,1,0)	7658.14	11542.71	46.27	0.01	0.01
121	Iraq	Navy	ses_model_0.1	3430.38	14864.99	46.27	0.00	0.00
122	Iraq	Navy	ses_model_0.3	3430.43	14865.19	46.27	0.00	0.00
123	Iraq	Navy	ses_model_0.5	3430.43	14865.19	46.27	0.00	0.00
124	Iraq	Navy	ETS(A,N,N)	3430.43	14865.19	46.27	0.00	0.00
125	Iraq	Navy	ses_model_0.7	3430.43	14865.19	46.27	0.00	0.00
126	Iraq	Navy	ses_model_0.9	3430.43	14865.19	46.27	0.00	0.00
127	Iraq	Navy	ARIMA(0,1,2)	3430.43	14865.19	46.27	0.00	0.00
128	Iraq	Navy	Regression with ARIMA(0,1,2) errors	3430.43	14865.20	46.27	0.00	0.00
129	Japan	Air Force	ETS(M,N,N)	641.87	0.26	5.97	0.00	0.00
130	Japan	Air Force	ses_model_0.9	642.96	0.26	5.97	0.17	0.17
131	Japan	Air Force	ses_model_0.7	653.08	0.27	5.97	1.75	1.75
132	Japan	Air Force	ses_model_0.5	698.90	0.29	5.97	8.88	8.88
133	Japan	Air Force	ARIMA(3,1,1)	733.74	0.30	5.97	14.31	14.31
134	Japan	Air Force	ses_model_0.3	857.79	0.35	5.97	33.64	33.64
135	Japan	Air Force	Regression with ARIMA(4,1,2) errors	1066.09	0.44	5.97	66.09	66.09
136	Japan	Air Force	ses_model_0.1	2378.80	0.97	5.97	270.60	270.60

137	Japan	Army	ses_model_0.1	495.36	0.15	5.97	0.00	0.00
138	Japan	Army	Regression with ARIMA(2,1,0) errors	551.25	0.17	5.97	11.28	11.28
139	Japan	Army	ARIMA(2,1,0)	851.48	0.26	5.97	71.89	71.89
140	Japan	Army	ETS(M,N,N)	890.22	0.27	5.97	79.71	79.71
141	Japan	Army	ses_model_0.9	892.10	0.27	5.97	80.09	80.09
142	Japan	Army	ses_model_0.7	897.18	0.27	5.97	81.12	81.12
143	Japan	Army	ses_model_0.3	901.34	0.27	5.97	81.96	81.96
144	Japan	Army	ses_model_0.5	902.84	0.27	5.97	82.26	82.26
145	Japan	Marine Corps	Regression with ARIMA(1,0,0) errors	3434.84	1.43	5.97	0.00	0.00
146	Japan	Marine Corps	ses_model_0.9	3519.93	1.46	5.97	2.48	2.48
147	Japan	Marine Corps	ETS(A,N,N)	3520.01	1.46	5.97	2.48	2.48
148	Japan	Marine Corps	ses_model_0.7	3522.62	1.46	5.97	2.56	2.56
149	Japan	Marine Corps	ARIMA(0,1,0)	3525.00	1.46	5.97	2.62	2.62
150	Japan	Marine Corps	ses_model_0.5	3527.98	1.46	5.97	2.71	2.71
151	Japan	Marine Corps	ses_model_0.3	3570.35	1.48	5.97	3.95	3.95
152	Japan	Marine Corps	ses_model_0.1	4152.34	1.72	5.97	20.89	20.89
153	Japan	Navy	Regression with ARIMA(0,1,0) errors	8918.92	2.38	5.97	0.00	0.00
154	Japan	Navy	ARIMA(0,1,0)	8994.43	2.40	5.97	0.85	0.85
155	Japan	Navy	ses_model_0.9	9083.16	2.42	5.97	1.84	1.84
156	Japan	Navy	ses_model_0.1	9143.11	2.44	5.97	2.51	2.51
157	Japan	Navy	ses_model_0.7	9278.83	2.48	5.97	4.04	4.04
158	Japan	Navy	ETS(M,N,N)	9285.45	2.48	5.97	4.11	4.11
159	Japan	Navy	ses_model_0.5	9479.58	2.53	5.97	6.29	6.29
160	Japan	Navy	ses_model_0.3	9625.82	2.57	5.97	7.93	7.93

161	Korea, South	Air Force	ses_model_0.5	397.39	0.20	10.45	0.00	0.00
162	Korea, South	Air Force	ses_model_0.7	404.70	0.20	10.45	1.84	1.84
163	Korea, South	Air Force	ses_model_0.3	412.71	0.20	10.45	3.85	3.85
164	Korea, South	Air Force	ses_model_0.9	417.12	0.21	10.45	4.96	4.96
165	Korea, South	Air Force	ETS(M,A,N)	471.20	0.23	10.45	18.57	18.57
166	Korea, South	Air Force	ses_model_0.1	620.16	0.31	10.45	56.06	56.06
167	Korea, South	Air Force	Regression with ARIMA(2,0,0) errors	629.60	0.31	10.45	58.43	58.43
168	Korea, South	Air Force	ARIMA(2,0,0) with non-zero mean	814.33	0.40	10.45	104.92	104.92
169	Korea, South	Army	ses_model_0.3	6648.90	0.62	10.45	0.00	0.00
170	Korea, South	Army	ses_model_0.5	6847.08	0.63	10.45	2.98	2.98
171	Korea, South	Army	ses_model_0.7	6987.13	0.65	10.45	5.09	5.09
172	Korea, South	Army	ses_model_0.9	7044.00	0.65	10.45	5.94	5.94
173	Korea, South	Army	ses_model_0.1	7694.19	0.71	10.45	15.72	15.72
174	Korea, South	Army	ARIMA(0,1,1)	8118.75	0.75	10.45	22.11	22.11
175	Korea, South	Army	ETS(M,A,N)	8419.55	0.78	10.45	26.63	26.63
176	Korea, South	Army	Regression with ARIMA(1,0,2) errors	12645.42	1.17	10.45	90.19	90.19
177	Korea, South	Marine Corps	ARIMA(0,1,1)	53.50	0.04	10.45	0.00	0.00
178	Korea, South	Marine Corps	ETS(M,N,N)	55.79	0.04	10.45	4.27	4.27
179	Korea, South	Marine Corps	ses_model_0.9	56.30	0.04	10.45	5.24	5.24
180	Korea, South	Marine Corps	ses_model_0.7	58.48	0.04	10.45	9.31	9.31
181	Korea, South	Marine Corps	ses_model_0.5	61.91	0.04	10.45	15.71	15.71
182	Korea, South	Marine Corps	ses_model_0.3	62.11	0.04	10.45	16.10	16.10
183	Korea, South	Marine Corps	ses_model_0.1	120.65	0.08	10.45	125.51	125.51

184	Korea, South	Marine Corps	Regression with ARIMA(2,0,0) errors	931.30	0.66	10.45	1640.74	1640.74
185	Korea, South	Navy	ETS(M,N,N)	79.14	0.08	10.45	0.00	0.00
186	Korea, South	Navy	ses_model_0.7	79.14	0.08	10.45	0.00	0.00
187	Korea, South	Navy	ses_model_0.9	79.14	0.08	10.45	0.00	0.00
188	Korea, South	Navy	ARIMA(0,1,0)	79.14	0.08	10.45	0.00	0.00
189	Korea, South	Navy	ses_model_0.5	79.92	0.08	10.45	0.98	0.98
190	Korea, South	Navy	ses_model_0.3	81.50	0.08	10.45	2.97	2.97
191	Korea, South	Navy	ses_model_0.1	99.73	0.09	10.45	26.01	26.01
192	Korea, South	Navy	Regression with ARIMA(2,0,0) errors	473.86	0.45	10.45	498.73	498.73
193	Kuwait	Air Force	ses_model_0.3	1215.78	13.68	41.79	0.00	0.00
194	Kuwait	Air Force	ses_model_0.5	1272.40	14.31	41.79	4.66	4.66
195	Kuwait	Air Force	ses_model_0.1	1430.67	16.09	41.79	17.68	17.68
196	Kuwait	Air Force	ses_model_0.7	1441.28	16.21	41.79	18.55	18.55
197	Kuwait	Air Force	ses_model_0.9	1676.69	18.86	41.79	37.91	37.91
198	Kuwait	Air Force	ETS(A,N,N)	1791.60	20.15	41.79	47.36	47.36
199	Kuwait	Air Force	Regression with ARIMA(0,1,0) errors	1791.71	20.15	41.79	47.37	47.37
200	Kuwait	Air Force	ARIMA(1,1,1) with drift	1886.31	21.22	41.79	55.15	55.15
201	Kuwait	Army	Regression with ARIMA(0,1,1) errors	16027.85	46.23	41.79	0.00	0.00
202	Kuwait	Army	ARIMA(0,1,1)	16035.97	46.25	41.79	0.05	0.05
203	Kuwait	Army	ETS(A,N,N)	16036.87	46.25	41.79	0.06	0.06
204	Kuwait	Army	ses_model_0.3	16045.32	46.28	41.79	0.11	0.11
205	Kuwait	Army	ses_model_0.5	16174.35	46.65	41.79	0.91	0.91

206	Kuwait	Army	ses_model_0.1	16231.66	46.81	41.79	1.27	1.27
207	Kuwait	Army	ses_model_0.7	16337.94	47.12	41.79	1.93	1.93
208	Kuwait	Army	ses_model_0.9	16524.05	47.66	41.79	3.10	3.10
209	Kuwait	Marine Corps	Regression with ARIMA(3,1,2) errors	1500.82	27.80	41.79	0.00	0.00
210	Kuwait	Marine Corps	ses_model_0.3	1513.86	28.04	41.79	0.87	0.87
211	Kuwait	Marine Corps	ses_model_0.5	1522.47	28.20	41.79	1.44	1.44
212	Kuwait	Marine Corps	ETS(A,N,N)	1528.61	28.32	41.79	1.85	1.85
213	Kuwait	Marine Corps	ses_model_0.1	1531.15	28.36	41.79	2.02	2.02
214	Kuwait	Marine Corps	ses_model_0.7	1531.43	28.37	41.79	2.04	2.04
215	Kuwait	Marine Corps	ses_model_0.9	1531.82	28.38	41.79	2.07	2.07
216	Kuwait	Marine Corps	ARIMA(3,1,3) with drift	1610.67	29.84	41.79	7.32	7.32
217	Kuwait	Navy	ses_model_0.3	1064.97	1538.30	41.79	0.00	0.00
218	Kuwait	Navy	ses_model_0.1	1065.50	1539.06	41.79	0.05	0.05
219	Kuwait	Navy	ses_model_0.5	1065.83	1539.53	41.79	0.08	0.08
220	Kuwait	Navy	ses_model_0.7	1066.53	1540.54	41.79	0.15	0.15
221	Kuwait	Navy	ses_model_0.9	1067.03	1541.26	41.79	0.19	0.19
222	Kuwait	Navy	ETS(A,N,N)	1067.21	1541.53	41.79	0.21	0.21
223	Kuwait	Navy	ARIMA(0,1,0)	1067.21	1541.53	41.79	0.21	0.21
224	Kuwait	Navy	Regression with ARIMA(0,1,0) errors	1067.22	1541.53	41.79	0.21	0.21
225	Qatar	Air Force	ARIMA(2,2,2)	5415.40	16564.77	67.16	0.00	0.00
226	Qatar	Air Force	Regression with ARIMA(0,1,0) errors	5453.83	16682.30	67.16	0.71	0.71
227	Qatar	Air Force	ETS(A,N,N)	5453.93	16682.61	67.16	0.71	0.71
228	Qatar	Air Force	ses_model_0.9	5454.03	16682.91	67.16	0.71	0.71

229	Qatar	Air Force	ses_model_0.7	5454.43	16684.15	67.16	0.72	0.72
230	Qatar	Air Force	ses_model_0.5	5455.62	16687.79	67.16	0.74	0.74
231	Qatar	Air Force	ses_model_0.3	5458.40	16696.30	67.16	0.79	0.79
232	Qatar	Air Force	ses_model_0.1	5464.14	16713.83	67.16	0.90	0.90
233	Qatar	Army	ETS(A,A,N)	902.21	272.76	67.16	0.00	0.00
234	Qatar	Army	ARIMA(3,1,0) with drift	928.44	280.69	67.16	2.91	2.91
235	Qatar	Army	Regression with ARIMA(3,1,0) errors	928.75	280.78	67.16	2.94	2.94
236	Qatar	Army	ses_model_0.7	1016.18	307.22	67.16	12.63	12.63
237	Qatar	Army	ses_model_0.5	1016.42	307.29	67.16	12.66	12.66
238	Qatar	Army	ses_model_0.9	1021.74	308.90	67.16	13.25	13.25
239	Qatar	Army	ses_model_0.3	1024.82	309.83	67.16	13.59	13.59
240	Qatar	Army	ses_model_0.1	1048.24	316.91	67.16	16.19	16.19
241	Qatar	Marine Corps	Regression with ARIMA(0,1,0) errors	74.95	99.94	67.16	0.00	0.00
242	Qatar	Marine Corps	ses_model_0.9	75.52	100.69	67.16	0.76	0.76
243	Qatar	Marine Corps	ses_model_0.7	76.65	102.21	67.16	2.27	2.27
244	Qatar	Marine Corps	ses_model_0.5	77.72	103.62	67.16	3.69	3.69
245	Qatar	Marine Corps	ses_model_0.3	78.41	104.55	67.16	4.61	4.61
246	Qatar	Marine Corps	ETS(A,N,N)	79.13	105.50	67.16	5.57	5.57
247	Qatar	Marine Corps	ARIMA(0,1,2)	79.30	105.73	67.16	5.79	5.79
248	Qatar	Marine Corps	ses_model_0.1	79.68	106.24	67.16	6.30	6.30
249	Qatar	Navy	ETS(A,A,N)	231.09	2002.79	67.16	0.00	0.00
250	Qatar	Navy	ses_model_0.9	244.55	2119.40	67.16	5.82	5.82
251	Qatar	Navy	ses_model_0.7	245.05	2123.76	67.16	6.04	6.04
252	Qatar	Navy	ses_model_0.5	245.75	2129.80	67.16	6.34	6.34

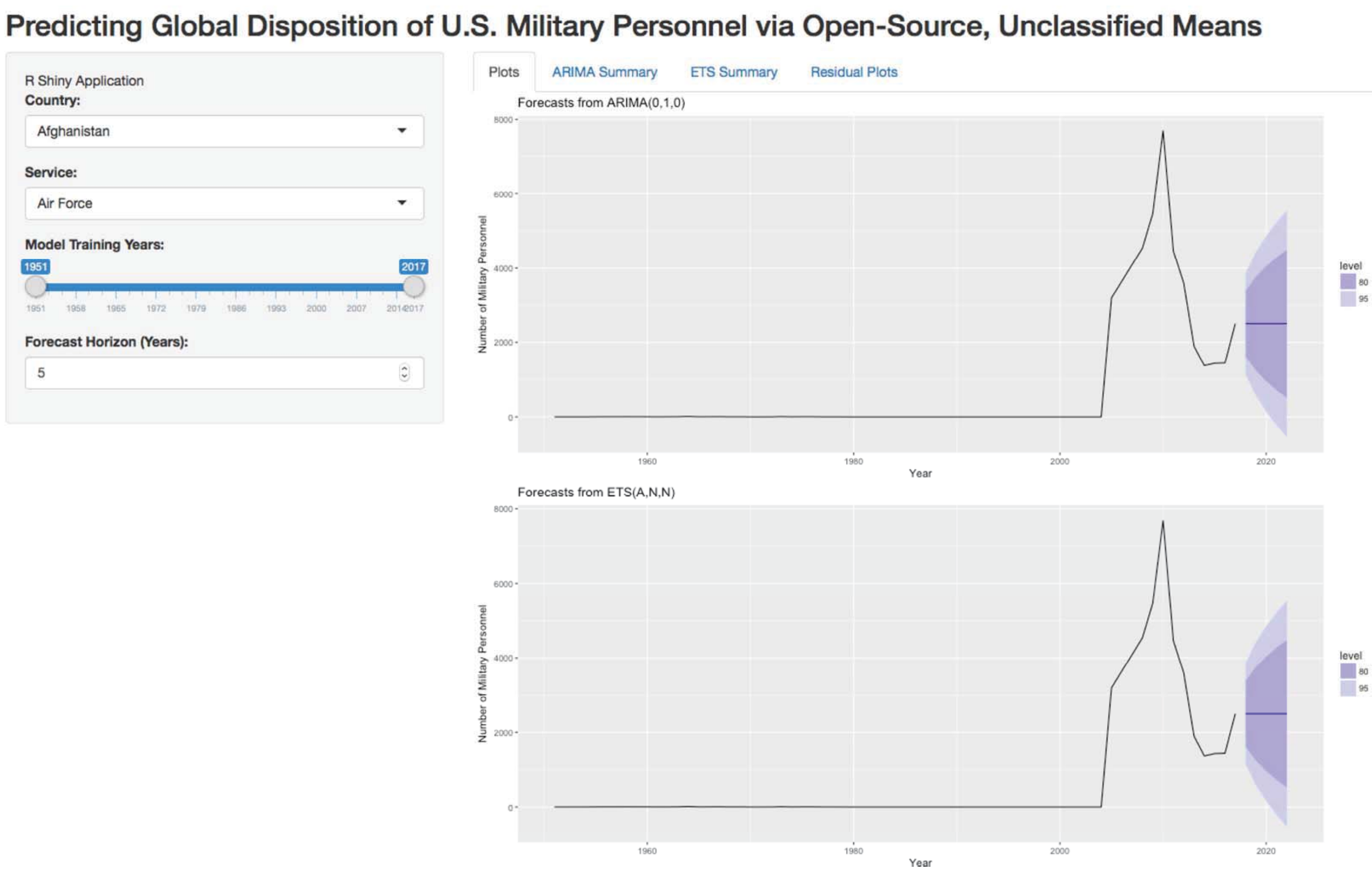
253	Qatar	Navy	ARIMA(1,0,3) with non-zero mean	246.39	2135.36	67.16	6.62	6.62
254	Qatar	Navy	ses_model_0.3	246.74	2138.39	67.16	6.77	6.77
255	Qatar	Navy	Regression with ARIMA(0,0,1) errors	247.49	2144.89	67.16	7.10	7.10
256	Qatar	Navy	ses_model_0.1	247.79	2147.51	67.16	7.23	7.23
257	Saudi Arabia	Air Force	ses_model_0.9	350.46	1.24	5.97	0.00	0.00
258	Saudi Arabia	Air Force	ses_model_0.7	1277.80	4.52	5.97	264.60	264.60
259	Saudi Arabia	Air Force	ses_model_0.1	1378.47	4.88	5.97	293.33	293.33
260	Saudi Arabia	Air Force	Regression with ARIMA(2,0,0) errors	1587.64	5.62	5.97	353.01	353.01
261	Saudi Arabia	Air Force	ARIMA(2,0,0) with non-zero mean	1625.20	5.75	5.97	363.73	363.73
262	Saudi Arabia	Air Force	ses_model_0.5	2114.97	7.49	5.97	503.48	503.48
263	Saudi Arabia	Air Force	ses_model_0.3	2427.89	8.59	5.97	592.76	592.76
264	Saudi Arabia	Air Force	ETS(M,A,N)	2524.68	8.94	5.97	620.38	620.38
265	Saudi Arabia	Army	ses_model_0.9	79.33	0.14	5.97	0.00	0.00
266	Saudi Arabia	Army	ses_model_0.7	86.86	0.15	5.97	9.49	9.49
267	Saudi Arabia	Army	ses_model_0.5	124.35	0.22	5.97	56.76	56.76
268	Saudi Arabia	Army	Regression with ARIMA(0,0,0) errors	173.51	0.30	5.97	118.73	118.73
269	Saudi Arabia	Army	ARIMA(0,0,0) with non-zero mean	240.80	0.42	5.97	203.56	203.56
270	Saudi Arabia	Army	ses_model_0.3	311.72	0.54	5.97	292.95	292.95
271	Saudi Arabia	Army	ETS(A,N,N)	601.43	1.04	5.97	658.16	658.16
272	Saudi Arabia	Army	ses_model_0.1	693.03	1.20	5.97	773.63	773.63

273	Saudi Arabia	Marine Corps	ARIMA(0,0,0) with zero mean	23.36	0.02	5.97	0.00	0.00
274	Saudi Arabia	Marine Corps	ses_model_0.5	124.63	0.11	5.97	433.59	433.59
275	Saudi Arabia	Marine Corps	ses_model_0.7	158.81	0.14	5.97	579.93	579.93
276	Saudi Arabia	Marine Corps	ses_model_0.9	196.58	0.18	5.97	741.61	741.61
277	Saudi Arabia	Marine Corps	ses_model_0.3	208.38	0.19	5.97	792.13	792.13
278	Saudi Arabia	Marine Corps	Regression with ARIMA(0,0,0) errors	562.06	0.50	5.97	2306.35	2306.35
279	Saudi Arabia	Marine Corps	ETS(A,N,N)	563.43	0.50	5.97	2312.23	2312.23
280	Saudi Arabia	Marine Corps	ses_model_0.1	882.86	0.79	5.97	3679.84	3679.84
281	Saudi Arabia	Navy	ses_model_0.9	4.90	0.18	5.97	0.00	0.00
282	Saudi Arabia	Navy	Regression with ARIMA(0,0,1) errors	7.73	0.29	5.97	57.68	57.68
283	Saudi Arabia	Navy	ETS(A,N,N)	14.07	0.53	5.97	187.07	187.07
284	Saudi Arabia	Navy	ARIMA(0,0,1) with non-zero mean	14.44	0.54	5.97	194.47	194.47
285	Saudi Arabia	Navy	ses_model_0.7	20.99	0.79	5.97	328.14	328.14
286	Saudi Arabia	Navy	ses_model_0.1	33.23	1.25	5.97	577.71	577.71
287	Saudi Arabia	Navy	ses_model_0.5	39.37	1.48	5.97	702.95	702.95
288	Saudi Arabia	Navy	ses_model_0.3	46.98	1.77	5.97	858.23	858.23
289	United Kingdom	Air Force	ses_model_0.7	407.81	0.20	5.97	0.00	0.00
290	United Kingdom	Air Force	ses_model_0.5	434.61	0.21	5.97	6.57	6.57
291	United Kingdom	Air Force	ses_model_0.9	437.96	0.21	5.97	7.39	7.39
292	United Kingdom	Air Force	ses_model_0.3	732.56	0.36	5.97	79.63	79.63
293	United Kingdom	Air Force	ARIMA(2,1,1)	2373.78	1.15	5.97	482.07	482.07
294	United Kingdom	Air Force	Regression with ARIMA(3,0,1) errors	3205.64	1.56	5.97	686.05	686.05

295	United Kingdom	Air Force	ETS(M,A,N)	5078.63	2.47	5.97	1145.33	1145.33
296	United Kingdom	Air Force	ses_model_0.1	5237.89	2.55	5.97	1184.38	1184.38
297	United Kingdom	Army	ses_model_0.1	69.97	0.26	5.97	0.00	0.00
298	United Kingdom	Army	ses_model_0.3	70.49	0.27	5.97	0.75	0.75
299	United Kingdom	Army	ses_model_0.5	79.95	0.30	5.97	14.27	14.27
300	United Kingdom	Army	ses_model_0.7	86.05	0.32	5.97	22.99	22.99
301	United Kingdom	Army	ses_model_0.9	91.76	0.35	5.97	31.14	31.14
302	United Kingdom	Army	ARIMA(0,1,0)	94.19	0.36	5.97	34.62	34.62
303	United Kingdom	Army	ETS(M,Ad,N)	98.55	0.37	5.97	40.86	40.86
304	United Kingdom	Army	Regression with ARIMA(2,0,2) errors	161.74	0.61	5.97	131.16	131.16
305	United Kingdom	Marine Corps	ses_model_0.9	33.48	0.77	5.97	0.00	0.00
306	United Kingdom	Marine Corps	ses_model_0.7	49.44	1.14	5.97	47.66	47.66
307	United Kingdom	Marine Corps	ses_model_0.5	66.68	1.54	5.97	99.13	99.13
308	United Kingdom	Marine Corps	ARIMA(0,1,1)	79.87	1.84	5.97	138.51	138.51
309	United Kingdom	Marine Corps	ETS(A,N,N)	81.43	1.88	5.97	143.20	143.20
310	United Kingdom	Marine Corps	ses_model_0.3	91.46	2.11	5.97	173.14	173.14
311	United Kingdom	Marine Corps	Regression with ARIMA(2,0,0) errors	156.88	3.62	5.97	368.52	368.52
312	United Kingdom	Marine Corps	ses_model_0.1	159.89	3.69	5.97	377.49	377.49
313	United Kingdom	Navy	ETS(M,A,N)	111.60	0.07	5.97	0.00	0.00
314	United Kingdom	Navy	Regression with ARIMA(0,0,0) errors	306.38	0.19	5.97	174.54	174.54
315	United Kingdom	Navy	ses_model_0.9	659.66	0.41	5.97	491.11	491.11
316	United Kingdom	Navy	ses_model_0.7	663.10	0.41	5.97	494.19	494.19
317	United Kingdom	Navy	ses_model_0.5	673.18	0.41	5.97	503.22	503.22
318	United Kingdom	Navy	ses_model_0.3	737.29	0.45	5.97	560.67	560.67

319	United Kingdom	Navy	ses_model_0.1	1220.42	0.75	5.97	993.59	993.59
320	United Kingdom	Navy	ARIMA(0,0,0) with non-zero mean	2323.36	1.43	5.97	1981.92	1981.92

Appendix B. R Shiny Application



Appendix C. Quad Chart

Predicting Global Disposition of U.S. Military Personnel via Open-Source, Unclassified Means

Captain Matthew T. Small
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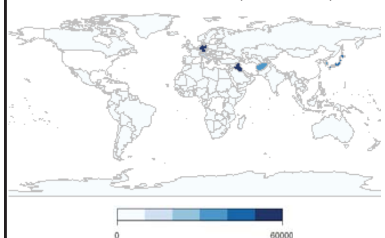
Department of Operational Sciences (ENS)
Air Force Institute of Technology

Sponsor: USTRANSCOM/JDPAC

Objective

- Develop and test a suite of predictive models to accurately forecast military force strength by country
- Determine which countries can be adequately forecasted so as to benefit USTRANSCOM demand forecasts
- Identify exogenous variables which may improve forecasting performance.

Average Yearly Disposition of OCONUS Personnel (2001-2017)



Modelling Framework

- Formulate three forecasting model types whose solutions yield accurate forecasts of military force strength by country and branch of service
  - Model 1: Exponential Smoothing Models
  - Model 2: ARIMA Models
  - Model 3: Regression with ARIMA Error Models

Related Literature

- Forecasting Models
- Econometric Models
- Regression Analysis

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Exponential Smoothing

$$\hat{y}_{t+h|T} = l_t + hb_t$$

where

$$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})$$

$$b_t = \mathrm{B}^*(l_t - l_{t-1})$$

Autoregressive Integrated Moving Average (ARIMA)

$$Z_t = \delta + a_t + \sum_{i=1}^{p} \phi_i Z_{t-i} + \sum_{j}^{q} \theta_j Z_{t-j}$$

Regression with ARIMA Errors

$$\hat{y}_t = \beta_0 + \beta_1 t + \beta_2 x_t + \epsilon_t$$

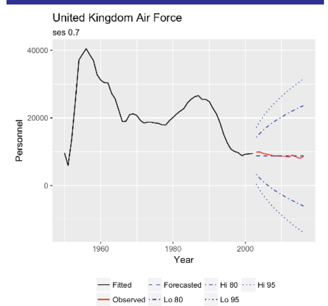
$$\hat{y}_t = \beta_0 + \beta_1 x_t + \Phi^{-1}(B)\omega_t$$

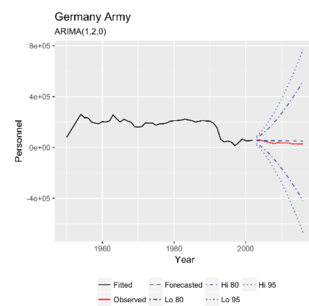
Forecasting Accuracy Metrics

$$\text{Mean Absolute Error (MAE)} = \frac{1}{T}\sum_{t=1}^{T} |y_t - \hat{y}_t|$$

$$\text{Mean Absolute Scaled Error (MASE)} = \frac{1}{T}\sum_{t=1}^{T} \frac{e_t}{\frac{1}{T-1}\sum_{t=2}^{T} |y_t - y_{t-1}|}$$

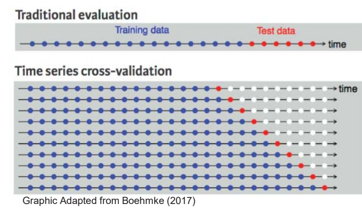
Selected Results





Analysis

- We determined which countries would be beneficial to forecast for USTRANSCOM needs by determining the variance of each country
- We applied our suite of models to the country
- We evaluated forecast accuracy using traditional and cross-validation accuracy to determine the best performing model for each country and branch



Graphic Adapted from Boehmke (2017)

Conclusions

- The exponential smoothing model with a high α-value performed well, in general; simpler models often yield accurate forecasts
- Countries with an enduring troop presence (e.g., Japan, Germany and Republic of Korea) were more conducive to accurate forecast development
- Countries without a substantial U.S. troop presence until the Global War on Terror (e.g. Iraq, Afghanistan) proved to be challenging to develop accurate models

Future Work

- Incorporate troop data into USTRANSCOM workload forecast as exogenous variables
- Incorporate DMDC Quarterly Data Releases into Forecasting Models

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14. ABSTRACT

Demand of USTRANSCOM assets are subject to fluctuations due to unforeseen circumstances such as war, conflict, natural disasters, and other calamities requiring the presence of military personnel. This study evaluates the use of forecasting models to predict the number of military personnel expected by branch and country each year. The expectation by USTRANSCOM is that accurate forecasts for the number of military personnel in each country can be leveraged to develop alternative transportation workload forecasts of demand of USTRANSCOM assets.
There was not a single model that performed best for all countries and branches of service. Each model was analyzed via the traditional 80/20 forecasting evaluation metric as well as a two-year horizon cross-validation metric. The exponential smoothing model with a high level of α performed quite well for many of the models, indicating that perhaps simpler models will still provide accurate forecasts. Further research is needed to determine whether incorporating forecasts of military personnel will improve the ability to forecast demand of USTRANSCOM assets.

15. SUBJECT TERMS

Time-Series Analysis, Exponential Smoothing, ARIMA, Regression with ARIMA Errors

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